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THESIS

MULTIPLE SENSOR CREDIT APPORTIONMENT

by

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June 2002

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Methods to individually allocate credit to multiple sensors assist Army decision makers during Objective Force development and integration. Sensor credit apportionment supports a knowledge-based common operating picture by providing a means to assess and compare the variety of automated and human sources that contribute to the common operating picture (U.S. Army White Paper, 2001). This thesis develops and assesses such a method. The method determines the contribution of individual sensors (person or platform that provides specific target information) to successful commander decision making. The method utilizes data fusion, decision analysis, and information quality to credit each sensor according to the benefit they provide a commander. A stochastic simulation provides the means to generate an environment in which to test and compare sensor performance, and to assess the credit apportionment method.

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MULTIPLE SENSOR CREDIT APPORTIONMENT

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ABSTRACT

Methods to individually allocate credit to multiple sensors assist Army decision makers during Objective Force development and integration. Sensor credit apportionment supports a knowledge-based common operating picture by providing a means to assess and compare the variety of automated and human sources that contribute to the common operating picture (U.S. Army White Paper, 2001). This thesis develops and assesses such a method. The method determines the contribution of individual sensors (persons or platforms that provide specific target information) to successful commander decision making. The method utilizes data fusion, decision analysis, and information quality to credit each sensor according to the benefit they provide a commander. A stochastic simulation provides the means to generate an environment in which to test and compare sensor performance, and to assess the credit apportionment method.

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EXECUTIVE SUMMARY

This thesis develops and assesses a method and working model to determine the contribution of individual sensors (persons or platforms that provide specific target information) to critical information gathering and to commander decision making. This thesis addresses credit apportionment (dividing and assigning) to specific sensors for satisfying an information requirement (Bauman, 2001).

A United States Army white paper, titled "Concepts for the Objective Force," states that the United States Army established Transformation as its focus. Transformation is a process changing the Army "…into a force that is strategically responsive and dominant at every point on the spectrum of conflict" (U.S. Army White Paper, 2001). The Army calls this future force the Objective Force.

The Objective Force anticipates near-perfect situational awareness: "…Objective Force Units will see first…" (U.S. Army White Paper, 2001). Seeing first includes "…detecting, identifying, and tracking the individual components of enemy units" (U.S. Army White Paper, 2001). Near-perfect situational awareness helps commanders make critical decisions using information based more on facts than assumptions, and also reduces the risk involved in decision making. Near-perfect situational awareness requires accurate, robust information sources (or sensors). It also requires a "…synthesized common picture of the battlefield, the common operational picture" (U.S. Army White Paper, 2001). Sensors, and the common

operational picture they create, make up critical components of the Objective Force.

Therefore, the Army needs methods to assess and compare sensors in terms of their contribution to the common operational picture. This thesis provides one method to accomplish such an evaluation.

The credit apportionment phenomenon of fusing information from separate, distinct sensors to create a common operational picture in order to inform a decision maker, and then apportion credit to the sensors according to their individual contributions to the decision, is an emerging, complex area of interest depicted in the figure below.

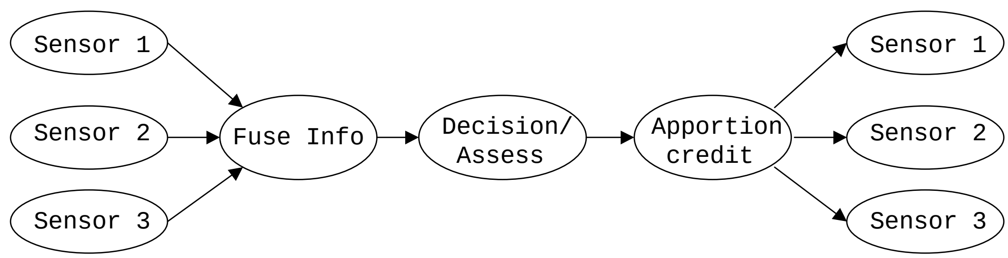

Figure 1. Multiple Sensor Credit Apportionment Phenomenon. (After Bauman, 2001)

Examination of the credit apportionment phenomenon first requires knowledge of its process. Then it demands developing a working model, or algorithm. Finally, it requires consideration of data requirements for the model.

A clearly defined understanding of the interactions at work in the credit apportionment phenomenon does not yet exist. As a result, a significant portion of this research effort attempts to communicate the essence of the apportioning credit phenomenon and its link to data fusion and information quality.

The assessment of the multiple sensor credit apportionment method includes conducting five experiments with various settings of three factors. The factors are the presence or absence of sensors, and the settings represent the sensor characteristics. Each experiment provides verification of the underlying calculations, as well as example results based on estimated input parameters. The primary input parameters include sensor characteristics and target attribute presence data.

Methods to individually allocate credit to multiple sensors, such as the method in this thesis, may assist Army decision makers during Objective Force development and integration. Being able to credit sources (or sensors) for the benefit they provide allows decision makers a means to compare sensors during development. In terms of force integration, methods to credit sensors also allow decision makers ways to find the best mix of sensors for a particular force.

I. INTRODUCTION

A. THESIS PURPOSE

This thesis develops and assesses a method and working model to determine the contribution of individual sensors (persons or platforms that provide specific target information) to critical information gathering and to commander decision making. This thesis addresses credit apportionment (dividing and assigning) to specific sensors for satisfying an information requirement (Bauman, 2001).

B. SIGNIFICANCE

A United States Army white paper, titled “Concepts for the Objective Force,” states that in the document, The Army Vision, the United States Army established Transformation as its focus. The Army Transformation is a process changing the Army “…into a force that is strategically responsive and dominant at every point on the spectrum of conflict” (U.S. Army White Paper, 2001). The Army calls this future force the Objective Force.

Methods to individually allocate credit to multiple sensors may assist Army decision makers during Objective Force development and integration. Seven force characteristics guide Objective Force development (U.S. Army White Paper, 2001):

- Responsive
- Deployable
- Agile
- Versatile
- Lethal

- Survivable
- Sustainable

The *Agile* characteristic represents possibly the most direct beneficiary of sensor credit apportionment methods. The white paper defines Objective Force *Agility* as the ability to quickly transition among various types of operations, such as from support operations to warfighting and back again (U.S. Army White Paper, 2001). The paper states information superiority through a knowledge-based common operational picture constitutes the essential element to enabling *Agility* in the Objective Force (U.S. Army White Paper, 2001). A “common operational picture” is a “…synthesized, common picture of the battlefield…” (U.S. Army White Paper, 2001). “Knowledge-based” means a common operational picture consists of “…near-real time…” information “…from a variety of automated and human sources…” (U.S. Army White Paper, 2001). Information superiority through a common operational picture enables *Agility*, because it expedites the decision-action cycle.

Sensor credit apportionment supports a knowledge-based common operating picture by providing a means to compare and assess the “…variety of automated and human sources…” that contribute to the common operating picture (U.S. Army White Paper, 2001).

Being able to credit sources (or sensors) for the benefit they provide allows decision makers a means to compare sensors during development. In terms of force integration, methods to credit sensors also allow decision makers ways to find the best mix of sensors for a particular force.

C. BACKGROUND

The United States Army Military Decision making Process consists of the following steps (Field Manual 101-5, 1997):

- Receipt of Mission
- Mission Analysis
- Course of Action Development
- Course of Action Analysis
- Course of Action Comparison
- Course of Action Approval
- Orders Production
- Rehearsal
- Execution and Assessment

This thesis focuses on Execution and Assessment. During Execution, a commander uses reports of Priority Information Requirements (PIR)—“information about the enemy”—in order to make execution decisions (Field Manual 101-5, 1997). The commander must make decisions with an incomplete view of the battlefield. The commander must choose PIRs carefully in order to gain critical information needed to make the best timely execution decision.

The Army acknowledges commanders must make execution decisions without a complete picture of battlefield reality. In Field Manual 101-5, the Army emphasizes commanders must “make critical decisions using information based more on assumptions than facts,” and they must “be resolute in accepting risk and be willing to make decisions based only on information immediately available” (Field Manual 101-5, 1997).

However, the future Army Objective Force anticipates near-perfect situational awareness: "At the tactical level, Objective Force Units will see first, understand first, act first and finish decisively as the means to tactical success" (U.S. Army White Paper, 2001). Seeing first includes "…detecting, identifying, and tracking the individual components of enemy units" (U.S. Army White Paper, 2001). Near-perfect situational awareness helps commanders make critical decisions using information based more on facts than assumptions, and also reduces the risk involved in decision making. Near-perfect situational awareness requires accurate, robust information sources (or sensors). It also requires a "…synthesized common picture of the battlefield, the common operational picture." Sensors and the common operational picture they create make up critical components of the Objective Force (U.S. Army White Paper, 2001).

Therefore, the Army needs methods to assess and compare sensors in terms of their contribution to the common operational picture. This thesis provides one method to accomplish such an evaluation of the sensors.

D. KNOWLEDGE, ALGORITHMS, AND DATA

A framework to examine models and simulations implemented by the Training and Doctrine Command Analysis Center-Monterey (TRAC-Monterey) and the United States Army Materiel Systems Analysis Activity (AMSAA) examines "knowledge" of the modeled phenomenon, "algorithms" used, and "data" required. The question they ask is: what knowledge, algorithms, and data are needed to adequately represent the phenomenon?

The credit apportionment phenomenon of fusing information from separate, distinct sensors to create a clearer information picture in order to inform a decision maker, and then apportion credit to the sensors according to their individual contributions to the decision, is an emerging, complex area of interest depicted in the figure below.

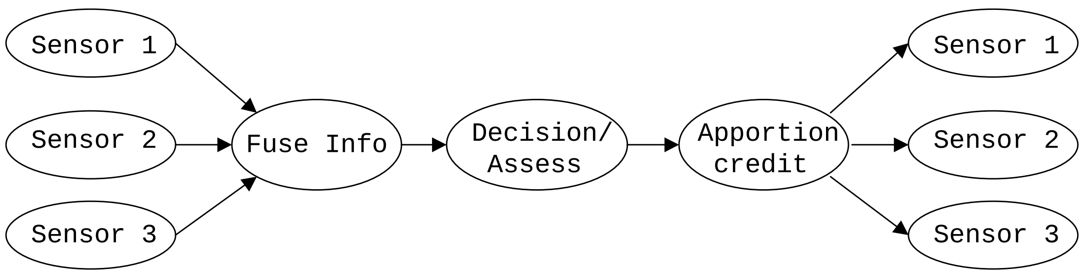

Figure 2. Multiple Sensor Credit Apportionment Phenomenon. (After Bauman, 2001)

Examination of the credit apportionment phenomenon first requires knowledge of its process. Then it demands developing a working model, or algorithm. Finally, it requires consideration of data requirements for the model.

1. Knowledge

Very little published information exists about multiple sensor credit apportionment, and a clearly defined understanding of the processes at work in the credit apportionment phenomenon does not currently exist. As a result, a significant portion of this research effort attempts to communicate the essence of the apportioning credit phenomenon and its link to data fusion and information quality (both discussed later in this section).

2. Algorithm

This thesis focuses on the development of an appropriate algorithm that fuses detection information from

independent sources while considering information quality in order to make a decision, assess the decision, and apportion credit. This complex and detailed algorithm forms the basis for a computer simulation.

Three model development steps make up the algorithm development process for this thesis:

- determine sensor detection capabilities,
- determine information quality each sensor provides,
- fuse detection capabilities and information value from multiple sensors.

a. Determine Sensor Detection Capabilities

The first model development step provides the foundation of the sensor credit method. The contribution of individual sensors ultimately traces back to their basic target detection capabilities. In order to determine sensor target detection capabilities, the sensor requires the presence probability (probability a target is present) of some type of target. In addition, sensor target detection capabilities require sensor detection capabilities of target attributes (a sensor only detects a target by detecting its attributes.) A target inherently possesses some measurable attributes (size, shape, location, activity, etc.) that define it as a target. This study investigates only single targets, and single detections by each sensor. Determining sensor detection capabilities addresses the process of combining the presence of a target, the presence of target attributes, and the sensor's ability to detect those attributes.

b. Determine Each Sensor's Information Quality

The second model development step determines how much value the sensors' detection information holds for a commander by calculating an information quality value for each sensor. Knowing a sensor's detection capability fails to provide enough basis to determine its contribution to satisfying an information requirement. Therefore, it is important to know whether the detection information holds any value to a commander. Dr. Walter Perry, RAND Corporation, states, "Information has value if it informs the commander and thereby adds to his knowledge of the combat situation" (Perry, 2000). He also states that information quality consists of accuracy, timeliness, and completeness (Perry, 2000). His component breakdown of information quality into accuracy, timeliness, and completeness forms the basis of the second step (determining information quality each sensor provides) of the sensor credit apportionment method.

c. Fuse Information

The third model development step fuses the results from step one (sensor detection capabilities) and step two (sensor information quality) for multiple sensors. Fusing information in this manner from multiple sensors attempts to represent a commander's thought process of combining all available information to create a clearer battlefield common operational picture when deciding whether or not to execute a course of action. After fusing the information, a commander makes a decision based on the fused, sensor-provided information. The information yields

either a correct or an incorrect decision. A sensor that provides information leading to a correct decision receives credit for its contribution. Conversely, a sensor that provides information leading to an incorrect decision receives no credit. (For this thesis, each sensor provides either good information or poor information. It cannot renege providing information.) The correctness of the commander's decision based on the actual target state and sensor-provided information provides the measure for comparing performance of various sensor combinations.

3. Data

Consideration of data requirements discovers that the credit apportionment model in this thesis depends heavily on input data (59 parameters when experimenting with three sensors). The majority (48 parameters) of the input parameters includes sensor characteristics and target attribute presence data. The other eleven parameters include parameters for generating a target presence probability from a uniform distribution, and parameters for generating initial information quality values from normal and exponential distributions.

For this thesis, it is sufficient that the input data are estimated. Therefore, while this model does not provide realistic performance of each sensor, it does provide insight about the relationships between sensors, an operational decision, and appropriate credit given to the sensors. Also, while this model uses estimated input data, further research and field experimentation may yield realistic input data. For this thesis, we estimated all the input parameters. Regardless of the "goodness" of the

input data, the multiple sensor credit apportionment method in this thesis provides insight about apportioning credit to sensors based on their performance.

E. SCOPE

This thesis focuses on the development and assessment of a sensor crediting simulation model. The model gives credit to each sensor for its role in assisting a commander make correct mission execution decisions.

This study uses independent sensors in order to simplify the credit apportionment. Independent sensors report information based solely on their own detections and inherent abilities. Commanders then fuse the sensors' independent information into a common operational picture.

Although this thesis develops a method to apportion credit to sensors, it does not develop an optimal sensor. Additionally, this thesis does not determine an optimal data fusion method. Finally, this thesis limits the definition of information quality to three components: accuracy, timeliness, and completeness. The next chapter provides definitions of the information components used in this thesis.

F. GENERAL METHODOLOGY

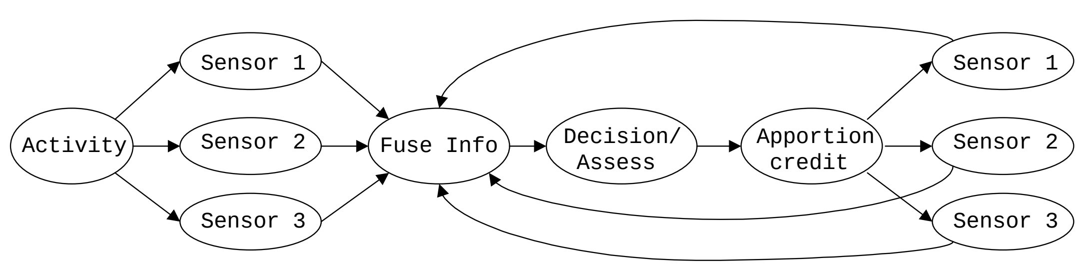

Figure 3. General Methodology. (After Bauman, 2001)

The figure above illustrates a general methodology for representing the multiple sensor credit apportionment

phenomenon. The Activity node represents an activity occurring in an area of interest. Various sensors detect or do not detect the activity. The sensors' reports are fused (Fuse Info node) in order to support a decision (Decision/Assess node) to execute a mission or to continue monitoring activity in the area of interest. Assessment of the execution decision (Decision/Assess node) reveals how valuable the sensors' information truly was. Each sensor's contribution to correct mission execution provides the basis for each sensor to receive appropriate credit in the Apportion Credit node. The arcs between the Apportion Credit node and the Fuse Info node represent learning (or experience) of the commander after each assessment and ranking of sensors. The commander's next decision will be flavored by his previous experience with the sensors. Previously successful sensors bias the commander toward favoring their results. Similarly, previously unsuccessful sensors bias the commander away from favoring their results. For this thesis, however, we assume an unbiased commander for all decisions (no learning or experience).

II. MODEL DEVELOPMENT

A. OVERVIEW

Combat models and simulations traditionally develop algorithms and code that acceptably represent physics-based phenomena. Specifically these algorithms calculate, or determine, line of sight, detection probability, successful engagement probability, or attrition rates. These phenomena, critical to the conduct of force-on-force modeling, are well documented in numerous accepted models.

However, recent interest in combat modeling development mirrors the Army Transformation addressed in the previous chapter. One of the areas of interest is data fusion—an extremely complex phenomenon. A human being stands as the best example of effective data fusion:

> Humans naturally apply this ability to combine data (sight, sound, scent, touch) from the body's sensors (eyes, ears, nose, fingers) with prior knowledge to assess the world and the events occurring about them. Because the human senses measure different physical phenomenon over different spatial volumes with different measurement characteristics, this process is both complex and adaptive. The conversion of the data…into a meaningful perception of the environment requires a large number of distinct intelligence processes and a base of knowledge sufficient to interpret the meaning of the properly combined data (Waltz and Llinas, 1990).

As mentioned earlier, the Army's desire to develop a battlefield common operational picture leads to the current interest in data fusion and credit apportionment. Data fusion represents the process required to achieve a common operational picture. Data fusion combines "…elements of

raw data from different sources into a single set of meaningful information that is of greater benefit than the sum of its contributing parts" (Waltz and Llinas, 1990). The Objective Force common operational picture is the "…single set of meaningful information…" desired by military commanders to expedite the decision-action cycle (Waltz and Llinas, 1990).

Fusion of information, or data, from multiple sensors directly leads to a common operational picture, while multiple sensor credit apportionment provides a method to know which sensors provide beneficial input to the common operational picture.

B. GENERAL MODEL

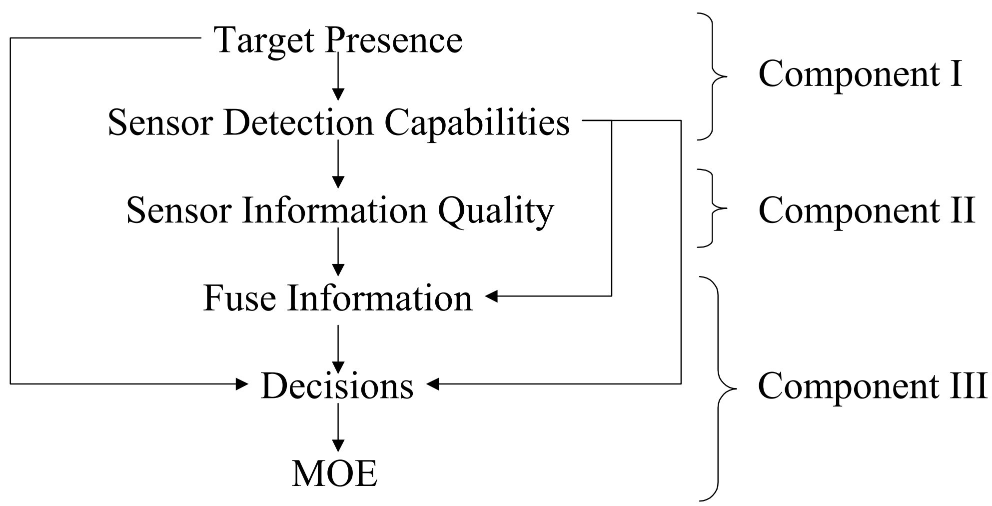

Figure 4. General Credit Apportionment Model

The figure above summarizes the credit apportionment model for this thesis. The following list displays the subcomponents of the general credit apportionment model shown above.

- Target Presence
  - generate target presence probability
  - calculate attribute presence probability

- Sensor Detection Capabilities
    - calculate probability sensor detects attributes
    - calculate probability sensor detects target
- Sensor Information Quality
    - define sensor detection outcome
    - define expected return value
    - define information quality components
    - generate sensor information accuracy
    - generate sensor information timeliness
    - calculate sensor information completeness
    - calculate total information quality for each sensor
- Fuse Information
    - define and illustrate decision tree
- Decisions
    - generate actual target state
    - generate sensor "decision" of the target state
    - calculate commander's decision
- Measure of Effectiveness (MOE)
    - count number of times actual target state, sensor "decision", and commander's decision all agree

The figure below provides a more detailed look at the credit apportionment model.

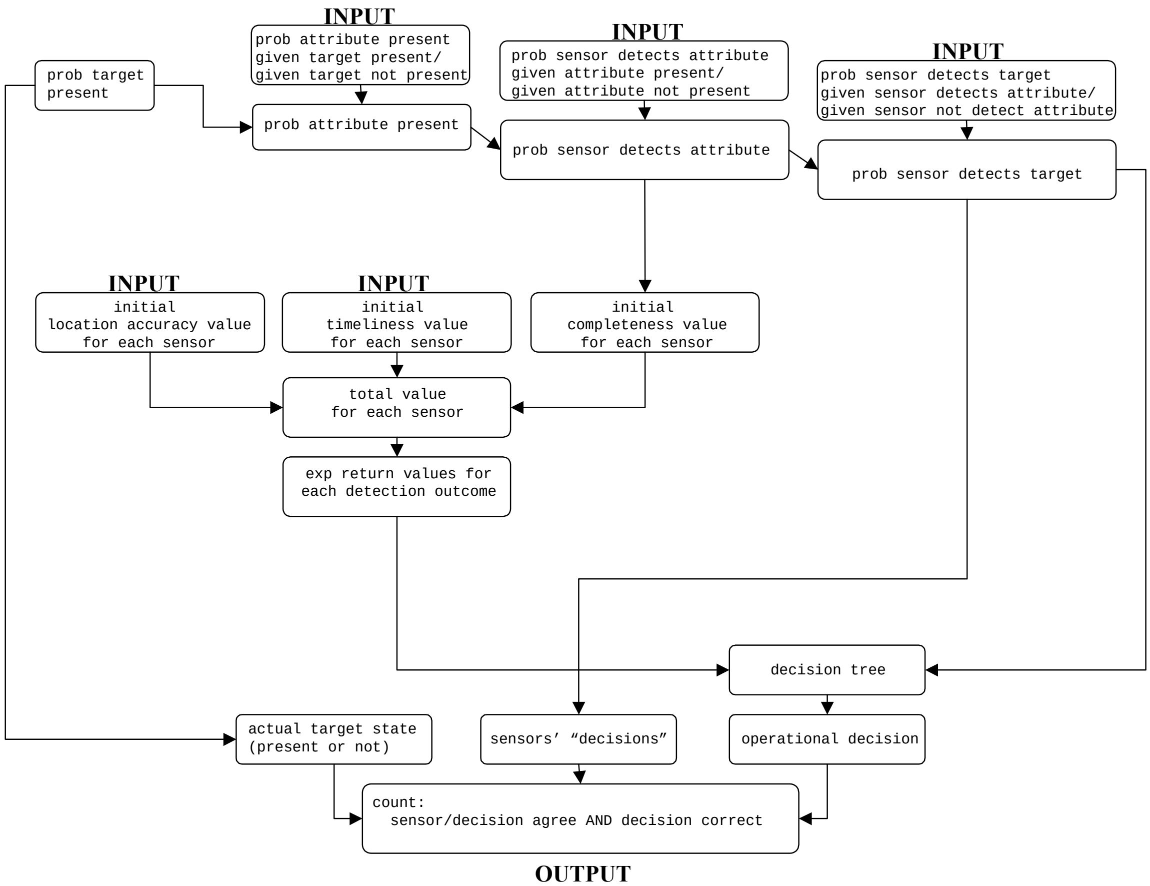

Figure 5. Detailed Credit Apportionment Model

The figure below illustrates the three components that make up the model.

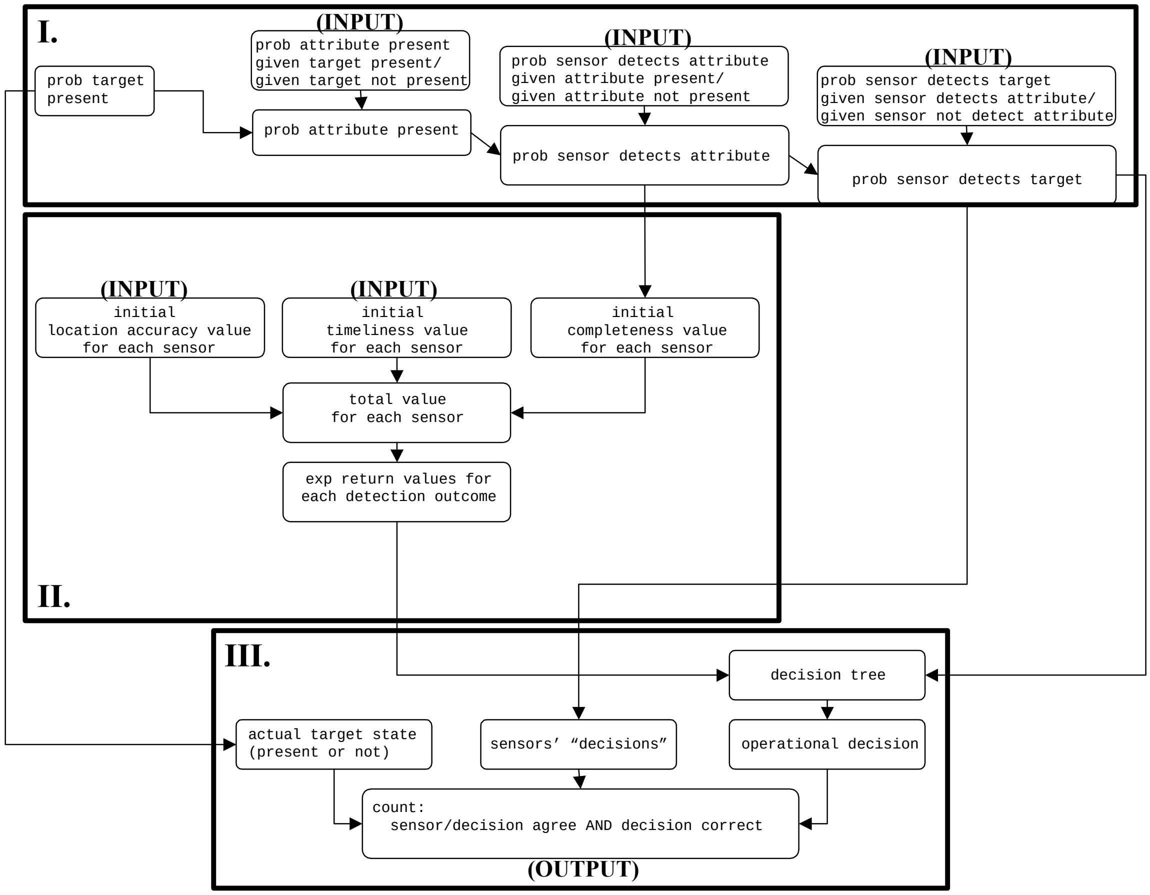

Figure 6. Credit Apportionment Model Components

Component I consists of sensor and target input. Component I includes Target Presence and Sensor Detection Capabilities from the general model presented above. Similarly Component II consists of information quality input, and it includes Sensor Information Quality from the general model. Component III consists of decisions and output, and it includes Fuse Information, Decisions, and MOE from the general model.

C. MODEL COMPONENT I, SENSOR INPUT

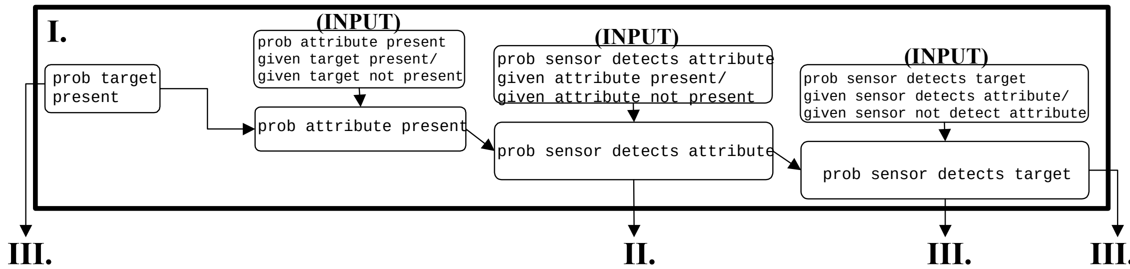

Figure 7. Model Component I, Sensor Input

1. Target Presence

The Law of Total Probability, $\Pr(B) = \Pr(B \mid A_1) * \Pr(A_1) + \cdots + \Pr(B \mid A_k) * \Pr(A_k)$, establishes the basis of Model Component I (Devore, 2000). The outputs of Model Component I, sensor detection probabilities, make up part of the input for Components II and III.

a. Target Presence Probability

To obtain sensor detection probabilities, we begin with the probability a target (threat entity) is present, $\Pr(\text{target present})$. Its value comes from a $\text{uniform}(\text{a} = 0.0, \text{b} = 0.75)$ draw. We keep those parameters constant for this thesis, but any combination of parameters between a=0.0 and b=1.0 are appropriate for this model. For each replication a random draw generates the probability a target is present (available for detection). The probability a target is present also becomes input for Model Component III for determining the actual target state.

b. Attribute Presence Probability

Next we calculate the probability a target attribute is present, $\Pr(\text{attribute present})$, using the law of total

probability. As stated previously, a target inherently possesses some measurable attributes (size, shape, location, activity, etc.) that define it as a target. Therefore, the probability an attribute is present is a function of whether the target is present or not. However, presence of a target attribute does not guarantee target presence.

$$\begin{aligned}\Pr(\text{attribute present}) = {} & \Pr(\text{attribute present} \mid \text{target present}) * \\ & \Pr(\text{target present}) + \\ & \Pr(\text{attribute present} \mid \text{target NOT present}) * \\ & \Pr(\text{target NOT present})\end{aligned}$$

For this model, the two conditional probabilities in the previous equation are prior probabilities obtained from a draw from a triangle distribution. We estimated the triangle distribution's parameters (Appendix B). Experimentation or historical data should provide more realistic values; however, the triangle distribution provides reasonable values in the "…absence of data…" (Law and Kelton, 2000).

We calculate $\Pr(\text{attribute NOT present})$ similarly:

$$\begin{aligned}\Pr(\text{attribute NOT present}) = {} & \Pr(\text{attribute NOT present} \mid \text{target present}) * \\ & \Pr(\text{target present}) + \\ & \Pr(\text{attribute NOT present} \mid \text{target NOT present}) * \\ & \Pr(\text{target NOT present})\end{aligned}$$

2. Sensor Detection Capabilities

a. Probability Sensor Detects Attributes

Next we use $\Pr(\text{attribute present})$ and $\Pr(\text{attribute NOT present})$ to calculate the probability a sensor detects a target attribute, $\Pr(\text{sensor detects attribute})$. A sensor is any person or

platform that provides specific target information. The probability a sensor detects an attribute is a function of whether the attribute is present or not. However, detection of an attribute does not guarantee an attribute is actually present. As before, we use the law of total probability:

$$\begin{aligned}\Pr(\text{sensor detects attribute}) = {} & \Pr(\text{sensor detects attribute} \mid \text{attribute present}) * \\ & \Pr(\text{attribute present}) + \\ & \Pr(\text{sensor detects attribute} \mid \text{attribute NOT present}) * \\ & \Pr(\text{attribute NOT present})\end{aligned}$$

Sensor specifications obtained from experimental data make up the conditional probabilities in the equations.

We calculate $\Pr(\text{sensor NOT detect attribute})$ similarly:

$$\begin{aligned}\Pr(\text{sensor NOT detect attribute}) = {} & \Pr(\text{sensor NOT detect attribute} \mid \text{attribute present}) * \\ & \Pr(\text{attribute present}) + \\ & \Pr(\text{sensor NOT detect attribute} \mid \text{attribute NOT present}) * \\ & \Pr(\text{attribute NOT present})\end{aligned}$$

The probability a sensor detects a target attribute becomes input to Model Component II for determining initial information completeness values for each sensor.

b. Probability Sensor Detects Target

The sensor target detection probabilities represent a sensor's "decision" about whether a target actually exists. The target may or may not actually be present, so a sensor's "decision" may or may not be correct. In order to determine the sensor target detection

probabilities, $\Pr(\text{sensor detects target})$, we use $\Pr(\text{sensor detects attribute})$ and $\Pr(\text{sensor NOT detect attribute})$ from above. Again sensor specifications obtained from experimental data make up the conditional probabilities below. Using the law of total probability:

$$\begin{aligned}\Pr(\text{sensor detects target}) = {} & \Pr(\text{sensor detects target} \mid \text{sensor detects attribute}) * \\ & \Pr(\text{sensor detects attribute}) + \\ & \Pr(\text{sensor detects target} \mid \text{sensor NOT detect attribute}) * \\ & \Pr(\text{sensor NOT detect attribute})\end{aligned}$$

The sensor detection probabilities become input to Model Component III for determining each sensor's "decision" about the presence of a target, and as one input for the decision tree.

D. MODEL COMPONENT II, INFORMATION QUALITY INPUT

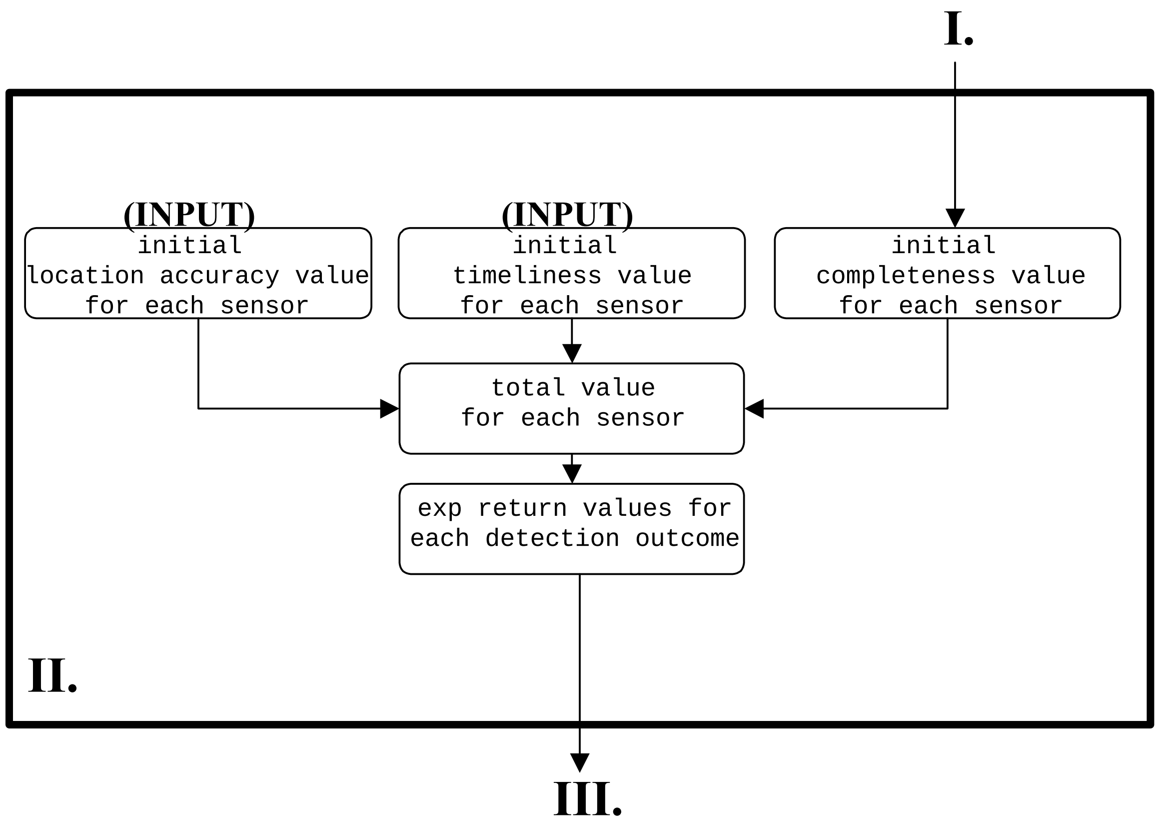

Figure 8. Model Component II, Information Quality Input

1. Sensor Information Quality

Component II takes sensors' target attributes detection capabilities and randomly generated values as inputs, and produces expected return values for use in a decision tree in Component III. The expected return value for each sensor detection outcome comes from a representation of information quality (defined below) calculated in this model component. We now define the sensor detection outcomes and expected return values in more detail.

a. *Sensor Detection Outcome*

First, what is a sensor detection outcome? If a specific application of this model includes two sensors, then an example sensor detection outcome is when both sensors detect a particular target, and their detection is correct. (For this research, a sensor detection outcome is either 'detect' or 'no detect'.) Another example is when the first sensor correctly detects a particular target, but the second sensor incorrectly does not detect it. Two sensors yield four different sensor detection outcomes. The number of mutually exclusive sensor detection outcomes is determined by 2^k, where k is the number of sensors.

b. *Expected Return Value*

Second, what is an expected return value for a sensor detection outcome? An expected return value in this model is the value of information provided by a sensor detection outcome.

Extending the example of two sensors from above, if both sensors correctly detect a particular target, then that sensor detection outcome has the largest expected return value. For this model, if both sensors correctly detect a particular target, then the expected return value has a large magnitude for a decision to attack the target. However, the same detection outcome (both sensors correctly detect the same target) yields a zero expected return value for a decision to not attack (because if both sensors detect the same target, the expected return for not striking should be very low, or even zero, for this model). One additional example: if one sensor incorrectly detects a target (target actually not present) and the second

sensor correctly does not detect a target, then the expected return value for that sensor detection outcome consists of only the information value for the second sensor (the sensor which reported correctly).

Therefore, we calculate expected return values as linear combinations of the information values of each sensor. As highlighted in the last example above, the linear combinations depend on the correctness of each sensor’s detection report. We refer to each sensor’s information value as the total information quality for that sensor. All the following portions of this section discuss the calculations needed to determine each sensor’s total information quality.

c. Information Quality Components

In this thesis we assume that three components determine information quality: accuracy, timeliness, and completeness (Perry, 2000). This thesis defines information quality components in the following manner: Accuracy encompasses how closely a sensor’s report of an entity’s location compares to the actual entity location. Timeliness indicates whether a commander receives information early enough or too late to act. Completeness indicates the degree to which a sensor correctly identifies an entity’s attributes, which, in turn, leads to accurate entity identification.

Sensor characteristics, operator and decision-maker training, time of day, and any of many other operational conditions influence all three of the information quality components. Therefore, we attempt to

group and estimate those operational influences as described in the following subsections.

d. Sensor Information Accuracy

To represent a sensor's accuracy in determining location, we first generate a $\text{normal}(\mu = 0, \sigma = 1)$ for each sensor to represent a miss distance (radial distance that represents the sensor's location error). If the resulting random miss distance is small (within a given range), then the location accuracy value is high (high values are good). Conversely, if the miss distance is large then the location accuracy value is low. We use a conditional setting to assign values to sensors with miss distances within set ranges. The ranges correspond to standard normal random variables (since we used the standard normal distribution). The best miss distances occur when $-0.4 \le z \le 0.4$, the next best occur when $0.4 < z \le 0.8$ or $-0.8 \le z < -0.4$, and so on. The worst miss distances occur for $z > 1.6$ or $z < -1.6$. For example, if a sensor's generated miss distance is $z = 0.35$, then the sensor receives an accuracy value of 8.0. And if a sensor's generated miss distance is $z = 1.7$, then the sensor receives an accuracy value of 0.0. We set the accuracy values in order to distinguish between a good miss distance (high value) and a poor miss distance (low value).

We use the normal distribution for the miss distance because previous applications have shown it is appropriate for representing location error (Law and Kelton, 2000). We use a mean of zero and standard deviation of one as the normal distribution's parameters (Appendix B) to illustrate one example setting of those

parameters. For this thesis, we held those constant, but they are variable.

e. Sensor Information Timeliness

To represent timeliness, we generate an $\text{exponential}(\lambda = 0.2)$ for each sensor to represent the amount of time (report time) from sensor detection to the commander's receipt of the information. If the elapsed time is small, then the timeliness value is high (high is good), and conversely. Like sensor accuracy above, we use a conditional setting to assign values to sensors with report times within set ranges. The ranges correspond to reasonable exponential variables. For this thesis the best report times occur when $x \leq 1.0$, the next best occur when $1.0 < x \leq 5.0$, and so on. The worst report times occur for $x > 25.0$. For example, if a sensor's generated report time is $x = 0.9$, then the sensor receives a timeliness value of 8.0. And if a sensor's generated report time is $x = 27.3$, then the sensor receives a timeliness value of 0.0. We set the timeliness values in order to distinguish between a good (low value) and a poor (high value) report time.

We use the exponential distribution based on its applicability to represent the time to complete a task (Law and Kelton, 2000). In this thesis, we use a constant rate of 0.2 as the exponential distribution's parameter (Appendix B) to illustrate one example setting of that parameter. Like sensor accuracy discussed above, this parameter is also variable.

f. Sensor Information Completeness

To represent completeness (degree to which the sensor correctly detects all target attributes), we input

each sensor’s probability of detecting each target attribute from Component I. Next, we compare a sensor’s attribute detection probability to a draw of a $\text{uniform}(a = 0, b = 1)$. If the random number is less than or equal to the detection probability, then that sensor detected the attribute. However, that does not mean the attribute is actually present. Therefore, we compare another $\text{uniform}(a = 0, b = 1)$ draw to the probability that the attribute is present in order to determine if the attribute is present. If the attribute is present and the sensor detects the attribute, the sensor receives positive value for correctly detecting the attribute. The sensor also receives positive value for correctly not detecting an attribute when an attribute is not present. The sensor receives no value for any incorrect attribute detections. Therefore, all incorrect attribute detections yield no value for a sensor, while each correct attribute detection yields positive value for the sensor. For example, if a sensor correctly detects one of the three attributes of a target, then the value it receives (value of 2.0) is less than a sensor that correctly detects all three target attributes (value of 8.0). The same values apply to the sensor if it correctly does not detect an attribute when an attribute is not present. In other words, the sensor receives value for being correct. Since this model uses three attributes, a sensor receives different levels of value based on how many attributes the sensor correctly detects (or correctly not detects).

g. *Total Information Quality For Each Sensor*

Next, we calculate the total value for each sensor by simply finding the sum of all the initial information component values:

$$total\ value\ sensor_1 = location\ accuracy_1 + timeliness_1 + completeness_1$$

These total values for each sensor combine with respect to the sensor detection outcomes to become the expected return values. For example, with two sensors, the detection outcome of both sensors correctly detecting the target has an expected return value equal to: $total\ value\ sensor_1 + total\ value\ sensor_2$. For the same example, the detection outcome of $sensor_1$ correctly detecting the target and $sensor_2$ incorrectly not detecting the target has an expected return value equal to: $total\ value\ sensor_1 + (total\ value\ sensor_2 = 0)$. Therefore, the outcome when both sensors agree and correctly detect the target receives the larger expected return value. The expected return values become an input for the decision tree in Model Component III.

E. MODEL COMPONENT III, DECISIONS AND OUTPUT

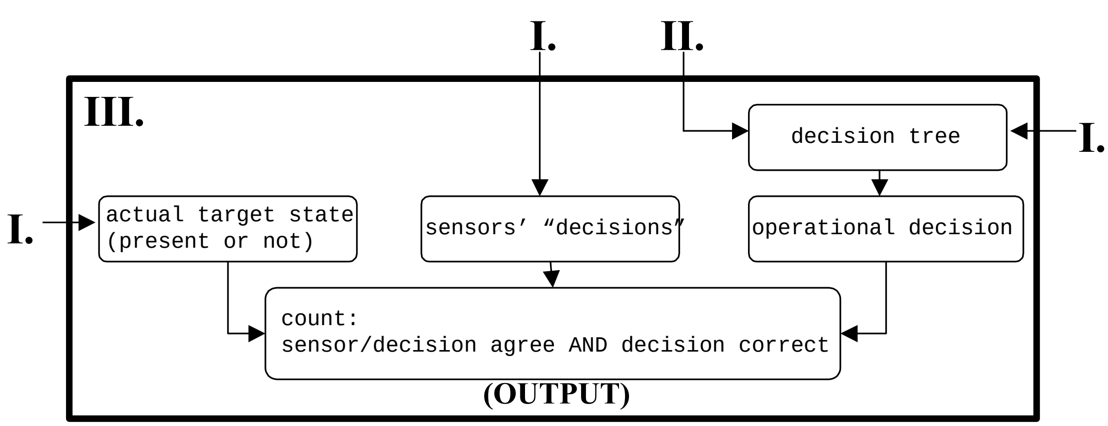

Figure 9. Model Component III, Decisions and Output

The third component of the model integrates the operational decision (from a decision tree), sensors' reports, and the actual target state. The output is the MOE for this thesis: the proportion of time the sensors' reports agree with the commander's decision, and they are both correct ('correct' meaning they agree with the actual target state). Further explanation of the output and MOE occurs later in this section.

1. Fuse Information

A decision tree performs data fusion of multiple sensors' detection capabilities and information quality values in order to represent a commander's decision given a common operational picture. The data fusion process yields a common operational picture that a commander uses to make an operational decision to attack or not. This model represents data fusion and decision making with a decision tree (Marshall and Oliver, 1995).

a. Decision Tree

The decision tree requires two sets of inputs: detection probabilities (from Model Component I) and expected return values (from Model Component II). The following decision tree illustrates how the detection probabilities (e.g. Pr(S1 detects), Pr(S2 detects), etc.) and expected return values (e.g. A, B, etc.) result in a decision to attack or not.

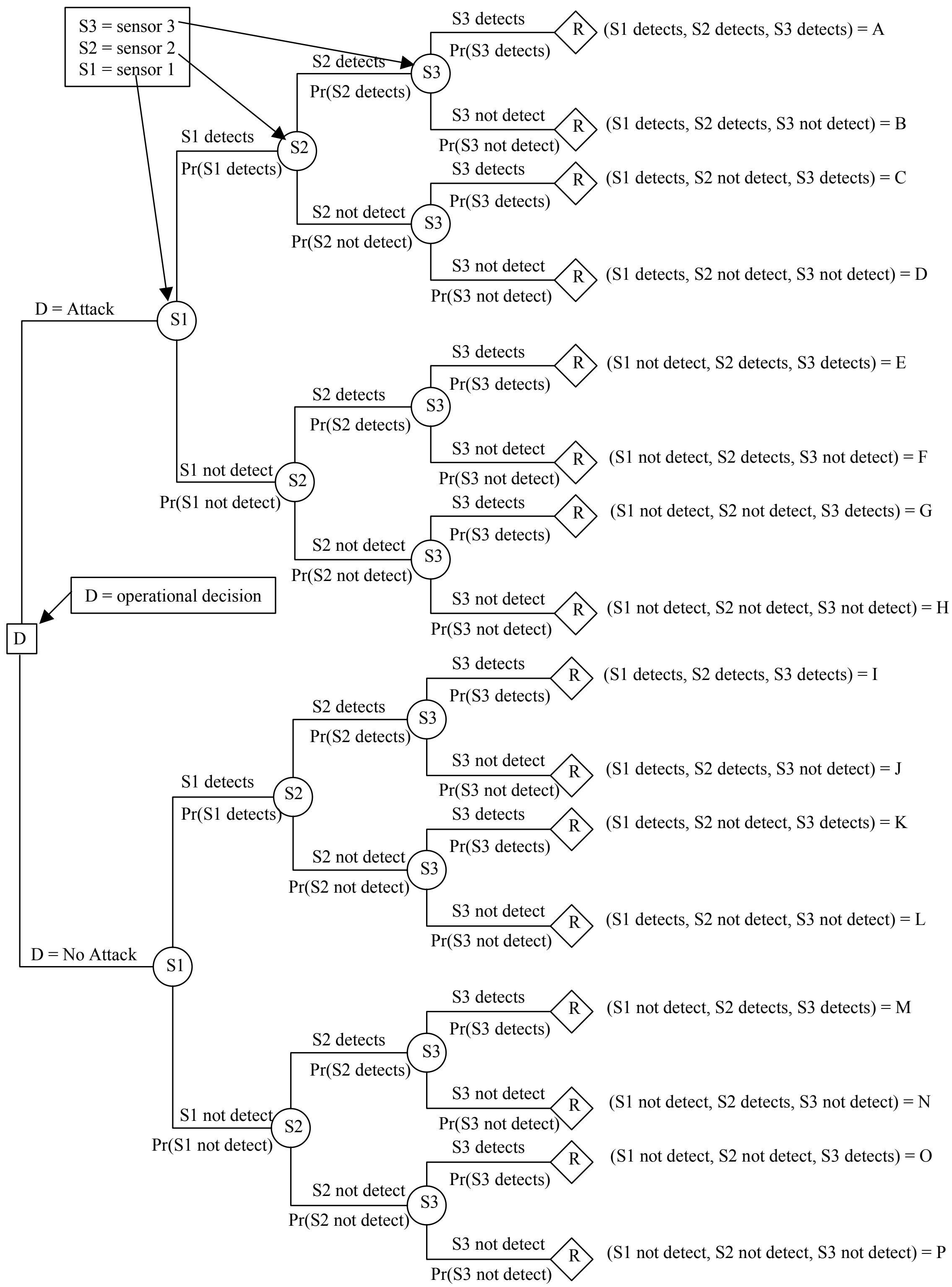

Figure 10. Decision Tree (After Marshall and Oliver, 1995)

First we calculate intermediate expected return values AB and CD:

$$AB = E\left[R(D = attack, S1 \text{ detects}, S2 \text{ detects})\right] = A * \Pr(S3 \text{ detects}) + B * \Pr(S3 \text{ not detect})$$
$$CD = E\left[R(D = attack, S1 \text{ detects}, S2 \text{ not detect})\right] = C * \Pr(S3 \text{ detects}) + D * \Pr(S3 \text{ not detect})$$

Next we calculate intermediate expected return values EF and GH:

$$EF = E\left[R(D = attack, S1 \text{ not detect}, S2 \text{ detects})\right] = E * \Pr(S3 \text{ detects}) + F * \Pr(S3 \text{ not detect})$$
$$GH = E\left[R(D = attack, S1 \text{ not detect}, S2 \text{ not detect})\right] = G * \Pr(S3 \text{ detects}) + H * \Pr(S3 \text{ not detect})$$

Next we calculate subsequent expected return values ABCD and EFGH:

$$ABCD = E\left[R(D = attack, S1 \text{ detects})\right] = AB * \Pr(S2 \text{ detects}) + CD * \Pr(S2 \text{ not detect})$$
$$EFGH = E\left[R(D = attack, S1 \text{ not detect})\right] = EF * \Pr(S2 \text{ detects}) + GH * \Pr(S2 \text{ not detect})$$

Finally we calculate the final expected return value ATTACK:

$$ATTACK = E\left[R(D = attack)\right] = ABCD * \Pr(S1 \text{ detects}) + EFGH * \Pr(S1 \text{ not detect})$$

Similar calculations yield final expected return value NO ATTACK:

$$NO\ ATTACK = E\left[R(D = no\ attack)\right] = IJKL * \Pr(S1 \text{ detects}) + MNOP * \Pr(S1 \text{ not detect})$$

The decision tree yields the expected return values for the decision to attack or not. If the expected return for attacking is larger than the expected return for not attacking, then the resulting operational decision is to attack. Alternately, if the expected return for attacking is less than or equal to the expected return for

not attacking, then the operational decision is to not attack.

2. Decisions

In order to assess the operational decision (correct or incorrect based on target presence), we compare the decision with the actual state of the target (whether or not a target is present).

a. Actual Target State

We determine the actual state of the target as follows: if a random draw of a $\mathrm{uniform}(a = 0, b = 1)$ is less than or equal to the probability a target is present (input from Model Component I), then the target is present. Otherwise, the target is not present. If the decision is to attack, and the target is actually present, then a correct operational decision was made.

b. Sensor "Decision" of the Target State

To assess each sensor's performance, we first calculate each sensor's "decision" about a target—whether the sensor says a target is present or not. For each sensor, we compare a random draw of a $\mathrm{uniform}(a = 0, b = 1)$ with the sensor's detection probability (input from Model Component I). If the random number is less than or equal to the detection probability, then the sensor "decides" it detected a target. Otherwise, the sensor "decides" it did not detect a target.

c. Commander's Operational Decision

In order to assess the operational decision (correct or incorrect based on target presence), we compare the decision with the actual state of the target (whether or not a target is present). For example, if the decision

is to attack, and the target is actually present, then the commander made a correct operational decision.

3. Measure of Effectiveness

a. Actual Target State, Sensor "Decision", and Commander's Decision All Agree

Our focus for this thesis is all the instances where a sensor agrees with the operational decision. This focus assists in the effort to evaluate how sensor performance supports the operational decision. A sensor and the operational decision agree when the sensor "decides" a target is present and the decision is to attack, or when the sensor "decides" a target is not present and the decision is to not attack.

In addition to the instances where a sensor agrees with the operational decision, we want to know when they agree correctly and when they agree incorrectly. In other words, we compare the actual target state (target present or not) with the sensor "decision" about the target, and with the operational decision to attack or not. This leads to the following mutually exclusive outcomes for any iteration of the model algorithm:

- Number Correct: measures the proportion of time the given sensors support the decision, and the sensors and decision are correct
- Number Incorrect: measures the proportion of time the given sensors support the decision, and the sensors and decision are incorrect
- Number Sensor Incorrect, but Decision Correct: measures the proportion of time the given sensors are all incorrect, but the decision is correct
- Number Sensor Correct, but Decision Incorrect: measures the proportion of time the given sensors are all correct, but the decision is incorrect.

The first of these, *Number Correct*, is the MOE for this thesis. It represents sensor performance with respect to the commander's decision. The MOE, *Number Correct*, combines the ideas of sensitivity ("…the proportion of positive results that agree with the true state") and specificity ("…the proportion of negative results that agree with the true state") to measure all results that agree with the true state (Bishop, Fienberg, and Holland, 1975). (The term, results, stands for instances where the sensors and commander's decision agree.) High MOE values represent good performance and low values represent poor performance.

The following figures represent what makes up each of the mutually exclusive outcomes listed above. The four figures below combine to form all the mutually exclusive and exhaustive outcomes for the model in this study.

The figure below displays all possible model results where the operational decision and at least one sensor's "decision" is correct for a situation with three sensors. Again, *Number Correct* measures the proportion of time the given sensors support the decision, and the sensors and decision are correct. *Number Correct* encompasses all the possible outcomes shown in the following figure.

Actual State	Decision	Sensor 1	Sensor 2	Sensor 3	Decision correct AND:
T	T	T	F	F	only sensor 1 correct
F	F	F	T	T	
T	T	F	T	F	only sensor 2 correct
F	F	T	F	T	
T	T	F	F	T	only sensor 3 correct
F	F	T	T	F	
T	T	T	T	F	only sensors 1 & 2 correct
F	F	F	F	T	
T	T	T	F	T	only sensors 1 & 3 correct
F	F	F	T	F	
T	T	F	T	T	only sensors 2 & 3 correct
F	F	T	F	F	
T	T	T	T	T	sensors 1, 2, & 3 correct
F	F	F	F	F	

Figure 11. Sensors/Decision Correct

The figure below displays all possible model results where the operational decision and at least one sensor's "decision" is incorrect for a situation with three sensors. Again, *Number Incorrect* measures the proportion of time the given sensors support the decision, but the sensors and decision are incorrect. *Number Incorrect* encompasses all the possible outcomes shown in the following figure.

Actual State	Decision	Sensor 1	Sensor 2	Sensor 3	Decision incorrect AND:
T	F	F	T	T	only sensor 1 incorrect
F	T	T	F	F	
T	F	T	F	T	only sensor 2 incorrect
F	T	F	T	F	
T	F	T	T	F	only sensor 3 incorrect
F	T	F	F	T	
T	F	F	F	T	only sensors 1 & 2 incorrect
F	T	T	T	F	
T	F	F	T	F	only sensors 1 & 3 incorrect
F	T	T	F	T	
T	F	T	F	F	only sensors 2 & 3 incorrect
F	T	F	T	T	
T	F	F	F	F	sensors 1, 2, & 3 incorrect
F	T	T	T	T	

Figure 12. Sensors/Decision Incorrect

The next figure displays the only possible model result where the operational decision is correct and all the sensors' "decisions" are incorrect for a situation with three sensors. Again, the *Number Sensor Incorrect, but Decision Correct* outcome measures the proportion of time the given sensors are all incorrect, but the decision is correct.

Actual State	Decision	Sensor 1	Sensor 2	Sensor 3	Decision correct AND:
T	T	F	F	F	all sensors incorrect
F	F	T	T	T	

Figure 13. Sensors Incorrect/Decision Correct

The following figure displays the only possible model result where the operational decision is incorrect and all the sensors' "decisions" are correct for a situation with three sensors. Again, the *Number Sensor Correct, but Decision Incorrect* outcome measures the proportion of time the given sensors are all correct, but the decision is incorrect.

Actual State	Decision	Sensor 1	Sensor 2	Sensor 3	Decision incorrect AND:
T	F	T	T	T	all sensors correct
F	T	F	F	F	

Figure 14. Sensors Correct/Decision Incorrect

F. SENSOR CREDIT APPORTIONMENT

Credit apportionment among multiple sensors is extremely complex. The following scenario attempts to provide an understanding of the complexity involved in modeling credit apportionment.

Assume a military commander faces a decision: to attack an entity or not. The commander receives information from three sensors: sensor A says the entity is an enemy tactical ballistic missile launcher, sensor B calls it an unknown object emanating heat, and sensor C says it's a vehicle of some kind with electronic emissions. Which sensor should the commander trust more? Should the commander trust all equally? What other information (experience, previous reports, target priority list) besides these sensor reports does the commander have to help form his decision? Is the commander biased toward one type of sensor based on previous experience? Is the commander (or sensor operator) well trained or experienced? How correct is each of the sensors' report? How reliable are the sensors? Are the sensors acting void of information, or are they passing their information among one another? Are they manned or unmanned sensors, or a combination of these items? What criteria do the sensors use to classify an entity as an enemy, unknown, or friend?

Assume the commander decides to attack the entity and the attack successfully eliminates an enemy missile launcher. Which sensor receives the most credit for the successful attack? Or, do any sensors receive any credit? How does the commander credit the sensors in his mind, thereby adjusting his experience base and influencing future decisions?

In this thesis we address a handful of the many complex relationships mentioned above. For example, we assume sensors do not share information with other sensors, assume no bias toward a sensor by the commander, assume no

learning or experience by the commander, and assume no other information available to aid in decision making.

After determining sensor performance, we apportion credit to sensors based on that performance. For example, a three-sensor combination of type 1 sensor, type 2 sensor, and type 3 sensor (annotated as ‘123’ in the following figure) provides a certain performance (approximately 860 in the figure below).

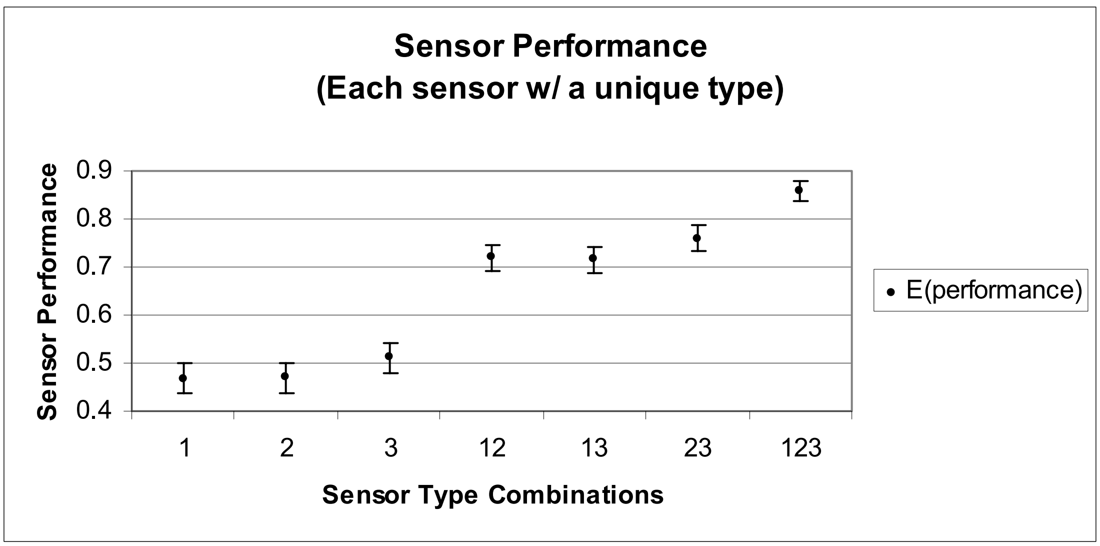

Figure 15. Sensor Credit Apportionment Example

Each individual sensor receives credit based on its individual performance. In the example above, the type 1 and type 2 sensors receive the least credit for their contribution to sensor type combination ‘123’ performance, and the type 3 sensor receives the most credit. In other words, the sensors receive a ranking of type 3, type 2, and type 1 in order from best to worst (with types 2 and 1 nearly identical). However, in this particular example, each of the sensors do not vary significantly at $\alpha = 0.05$, as indicated by the 95% confidence intervals shown above. In

general, sensors with larger performance means and smaller performance standard deviations receive more credit.

A brief discussion is warranted about what sensor "type" means. In this thesis, a sensor's specifications define its type. Typical general sensor types include a person, unmanned aerial vehicle (UAV), or satellite. However, each person possesses his or her own sensor specifications, so each person also makes up a separate type of sensor. Similarly, different UAV types or different satellite types all possess their own sensor specifications; therefore, each different UAV or satellite also makes up a separate type of sensor. Even with identical sensor specifications between two sensors, their performance varies due to randomness.

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III. SIMULATION RESULTS AND ANALYSIS

A. GENERAL SIMULATION INFORMATION

The simulation in this thesis uses up to three sensors of up to three possible types. Each simulation replication yields a single binary value among four mutually exclusive and exhaustive alternatives:

- The actual target state, operational decision, and sensors “decisions” agree (operational decision and sensors correct).
- The actual target state disagrees with the operational decision and sensors “decisions” (operational decision and sensors incorrect).
- The actual target state and operational decision agree, but the sensors “decisions” disagrees (operational decision correct, but sensors incorrect).
- The actual target state and sensors “decisions” agree, but the operational decision disagrees (operational decision incorrect, but sensors correct).

The first alternative above makes up the simulation measure of effectiveness (MOE) and the experiment’s response: the proportion of correct sensor and commander decisions to the total number of replications. This proportion represents sensor performance. As shown and explained in the previous chapter, the following figure displays all possible outcomes for the MOE (the figure shows a three sensor example).

Actual State	Decision	Sensor 1	Sensor 2	Sensor 3	Decision correct AND:
T	T	T	F	F	only sensor 1 correct
F	F	F	T	T	
T	T	F	T	F	only sensor 2 correct
F	F	T	F	T	
T	T	F	F	T	only sensor 3 correct
F	F	T	T	F	
T	T	T	T	F	only sensors 1 & 2 correct
F	F	F	F	T	
T	T	T	F	T	only sensors 1 & 3 correct
F	F	F	T	F	
T	T	F	T	T	only sensors 2 & 3 correct
F	F	T	F	F	
T	T	T	T	T	sensors 1, 2, & 3 correct
F	F	F	F	F	

Figure 16. Sensors/Decision Correct

Similar figures exist (figures 12, 13, and 14 in the previous chapter) for the other three mutually exclusive alternatives listed above. For each replication of each run of the simulation, exactly one of the outcomes from the four outcome figures occurs. Our primary interest in this study lies in those outcomes shown above. The MOE consists of only the total number of outcomes from the figure above that occur during each simulation run.

One run of the simulation consists of 1000 replications at identical initial settings for each replication. Each of the 1000 replications varies only by randomness. Each run yields a count out of 1000, or a proportion, for each of the mutually exclusive and exhaustive alternatives listed above. Therefore, the four alternatives' counts sum to one for each run. This simulation used 1000 replications in order to ensure a confidence interval width less than 0.1. An estimate for the number of replications required for an interval width of 0.1 yielded a value of approximately 384 replications.

However, since generating data from the simulation required little computing time, we chose 1000 replications (Devore, 2000).

The simulation settings encompass all user-supplied inputs such as sensor types, sensor specifications, and probability distribution parameters. The sensor types vary within each experiment. The sensor specifications and probability distribution parameters remain constant for all experiments. The sensor specifications used appear in Appendix A. The parameters for the probability distributions appear in Appendix B.

B. EXPERIMENTAL DESIGN

All the experiments consist of the three sensors as variables. Each sensor has four possible types: type 1, type 2, type 3, or ‘no sensor’. The experiment’s response is sensor performance (defined above).

Each of the experiments conducts a stand-alone look at a specific aspect of the relationship among the sensor types and their performance. The purpose of conducting the experiments in this manner is to allow for model face validation and verification rather than trying to determine which input variables are most significant in the model. Therefore, in order to conduct face validation and verification, this thesis assumes the input values in Appendix A represent realistic values.

All the experiments consist of seven runs, nine runs, or 19 runs, depending on the experiment type (discussed later in this chapter). The seven-run experiments use seven different sensor type combinations—one run for each combination, while the 19-run experiment uses 19 different

sensor type combinations. Reference Appendix C to view each experiment's design.

In all the experiments we assume all sensors involved are within detection range of a target if it is present. Also, we assume no multiple targets occur, and we assume a sensor only detects a single target once.

Each experiment's response represents sensor performance. High response represents good performance, and low response represents poor performance. The response (or sensor performance), measures the proportion of correct sensor and commander decisions to the total number of events (an event is one replication). For example, if a sensor and the commander agree a target is present, and if the target really is present, then they are correct. Conversely, if they agree a target is not present, and if the target really is not present, then they are also correct. If the number correct within a run is 350, then the sensor performance for that run is $\frac{350}{1000} = 0.350$. The average value of that run is then $n * p = 1000 * 0.350 = 350$.

C. EXPERIMENT A (ALL SENSORS OF SAME TYPE)

This experiment's purpose is to show that sensors of identical type provide equivalent, but not identical performance, due to inherent randomness. This characteristic models reality: two identical sensors perform similarly, but not identically, in separate tests under similar circumstances. Therefore, results from this experiment support face validation of this model.

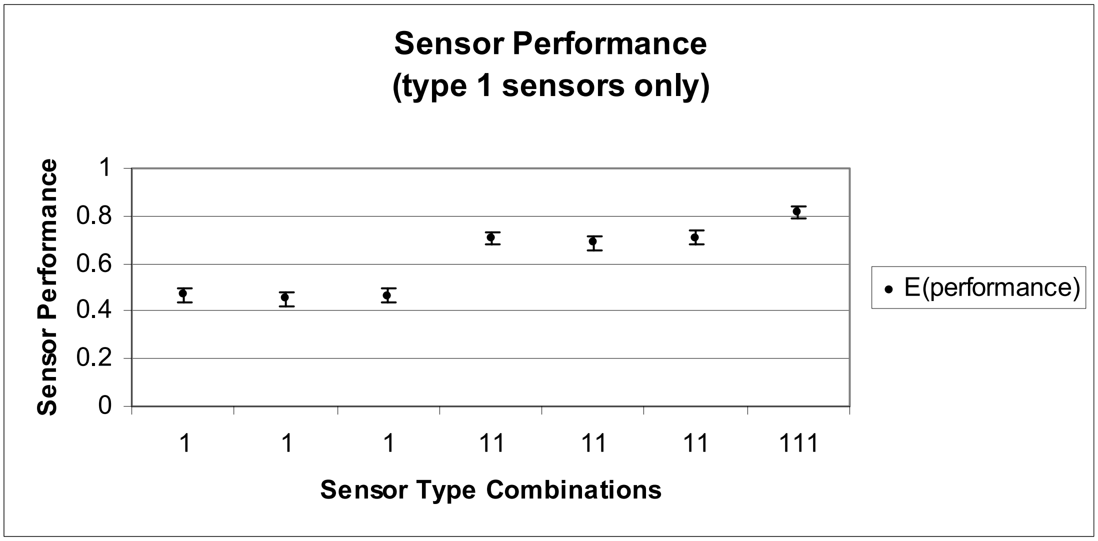

Figure 17. Sensor Performance (All Sensors of Type 1)

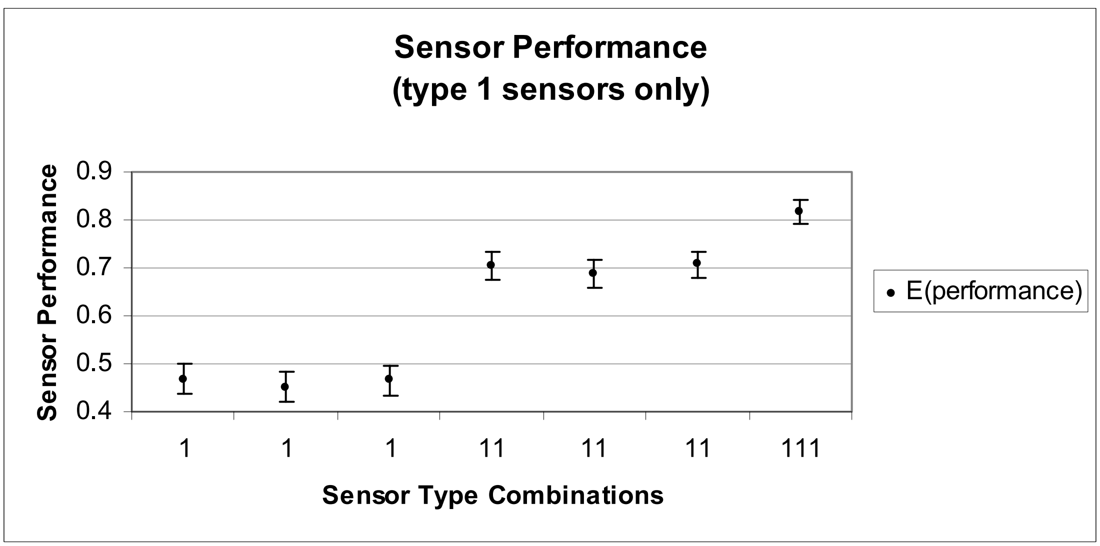

Figure 18. All Sensors of Type 1 (Zoom View)

Simulation Run	Sensor Combination	Sensor Type	Response Mean	95% CI Lower	95% CI Upper
1	Sensor 1	1	0.468	0.437	0.499
2	Sensor 2	1	0.452	0.421	0.483
3	Sensor 3	1	0.466	0.435	0.497
4	Sensors 1 & 2	1 & 1	0.706	0.677	0.733
5	Sensors 1 & 3	1 & 1	0.688	0.659	0.716
6	Sensors 2 & 3	1 & 1	0.708	0.679	0.735
7	Sensors 1 & 2 & 3	1 & 1 & 1	0.818	0.793	0.841

Table 1. Experiment A Summary Statistics

This experiment consists of a mix of three sensors of identical type as defined by each sensor's specifications. Appendix A contains the specifications for all sensor types used for this thesis.

The figures and table above show that different sensors of identical type yield similar performance over 1000 replications. In other words, runs 1, 2, and 3 illustrate that three different sensors of identical type produce response means that are not significantly different at $\alpha = 0.05$. Again, the response for all experiments represents sensor performance—large response values are better. Simulation run 1 consists of only sensor 1 set at type 1, run 2 consists of only sensor 2 also set at type 1, and run 3 consists of only sensor 3 set at type 1. Their performance after 1000 replications measured 0.468, 0.452, and 0.466, respectively. These results support the idea that different sensors of identical type produce similar performance over the long run. The differences in response means and confidence intervals occur due to randomness in

the model. Again, each replication begins with identical initial settings and varies only due to the randomness we input (Appendices A and B). The results from one replication do not carry forward to the next replication. The results from this experiment support common sense: if one sensor is identical to another, then both sensors' performance should agree over many replications.

The figures and table also support the idea that three sensors providing information to a commander lead to better performance over the long run than any of the individual sensors working alone. Indeed, this is the premise of data fusion. For example, the response mean of the three sensors combination is 0.818, while the response means of each individual sensor are 0.468, 0.452, and 0.466, respectively. In addition, the 95% confidence interval of three sensor combination shows over the long run, the worst (lowest) response is better than the best of any of the individual sensors alone. In other words, at $\alpha = 0.05$ their performance differs significantly.

D. EXPERIMENT B (EACH SENSOR OF UNIQUE TYPE)

This experiment's purpose is to compare the performance of each type of sensor by constraining each sensor to only one type. This experiment consists of three sensors of unique types. Each sensor maintains its type throughout the experiment. For instance, sensor 2 is always type 2 for this experiment.

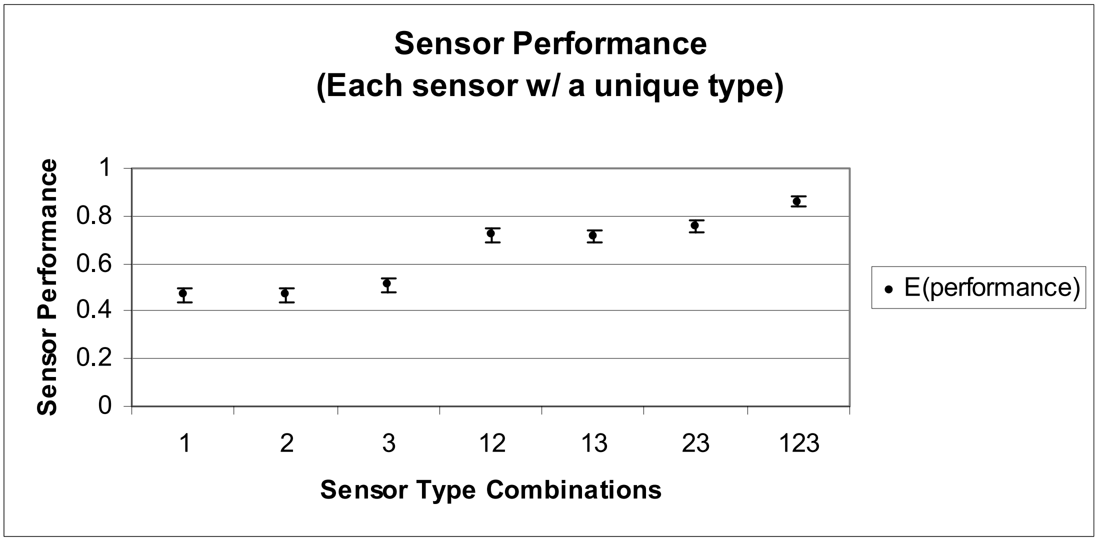

Figure 19.   Sensor Performance (1 Unique Type per Sensor)

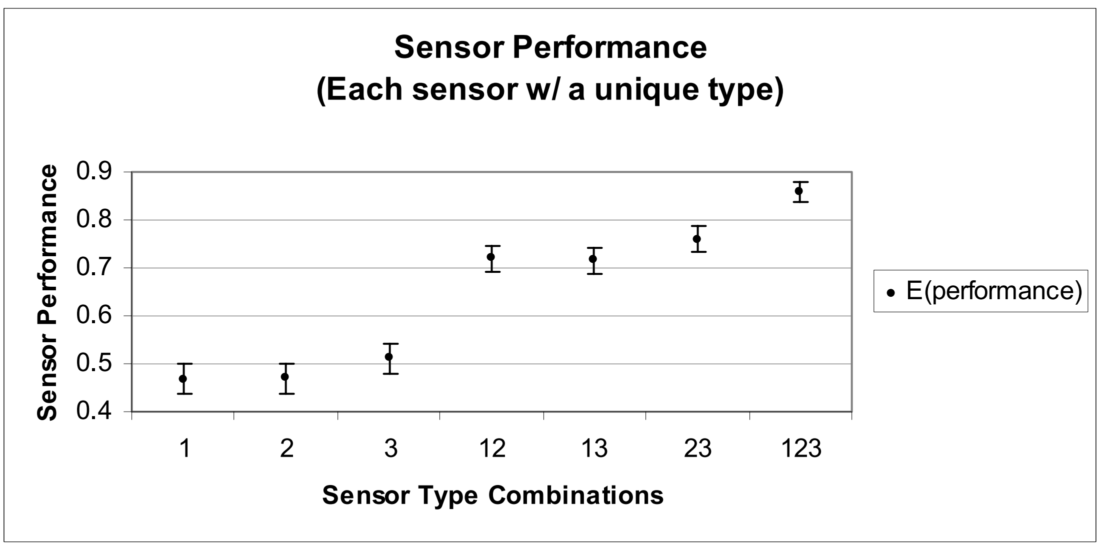

Figure 20.   1 Unique Type per Sensor (Zoom View)

Simulation Run	Sensor Combination	Sensor Type	Response Mean	95% CI Lower	95% CI Upper
1	Sensor 1	1	0.468	0.437	0.499
2	Sensor 2	2	0.469	0.438	0.500
3	Sensor 3	3	0.511	0.480	0.542
4	Sensors 1 & 2	1 & 2	0.719	0.690	0.746
5	Sensors 1 & 3	1 & 3	0.716	0.687	0.743
6	Sensors 2 & 3	2 & 3	0.760	0.733	0.785
7	Sensors 1 & 2 & 3	1 & 2 & 3	0.860	0.837	0.880

Table 2. Experiment B Summary Statistics

In this experiment, run 1 and run 2 show that a type 1 sensor performs very similarly (response means not significantly different at $\alpha = 0.05$) to a type 2 sensor even though their specifications differ: type 1 and 2 means of 0.468 and 0.469 and 95% confidence intervals of [0.437, 0.499] and [0.438, 0.500], respectively. A type 3 sensor appears to perform better than either of the other two: type 3 mean of 0.511 and 95% confidence interval of [0.480, 0.542]. However, at $\alpha = 0.05$, its mean does not differ significantly from sensor types 1 and 2.

The table and figures above continue to support the idea that multiple sensors providing information to a commander lead to better performance over the long run than any of the individual sensors working alone. Run 7 illustrates that sensor combination of type 1, 2, and 3 outperforms any of the other combinations with a mean of 0.860 and 95% confidence interval of [0.837, 0.880].

E. EXPERIMENT C (SENSOR COMBINATION ORDER)

This experiment addresses the concern of whether the order of sensor settings significantly affects the results. By ‘order’ we mean that a sensor type combination of type 1, 2, and 3, has a different order than a combination of type 3, 1, and 2. This experiment serves two purposes.

First, the experiment confirms the correctness of the model’s underlying calculations. Since sensors 1, 2, and 3 are all type 1 sensors during runs 1, 2, and 3, their individual performances should be similar but not identical, as randomness prevents identical performance from identical sensors. In other words, their individual performances are equivalent.

Second, the experiment eliminates the need for unnecessary experiment runs. Since sensors of the same type yield equivalent results, a sensor type combination of type 1, 2, and 3, for example, yields a result equivalent to the result of a type 3, 1, and 2 combination. Therefore, the ‘order’ of the sensor types does not significantly affect the results of the experiment.

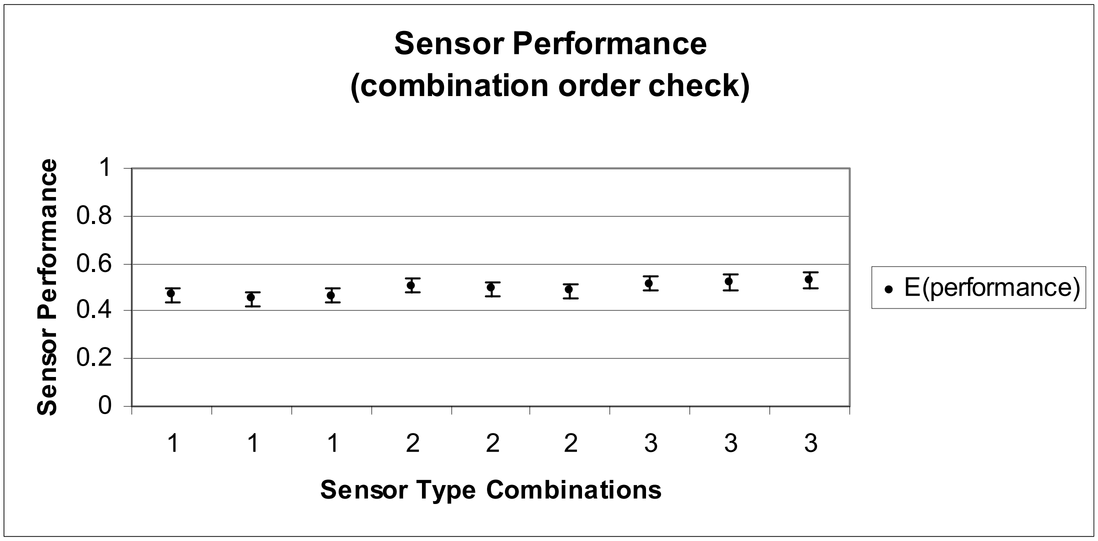

Figure 21. Sensor Performance (Check Combination Order)

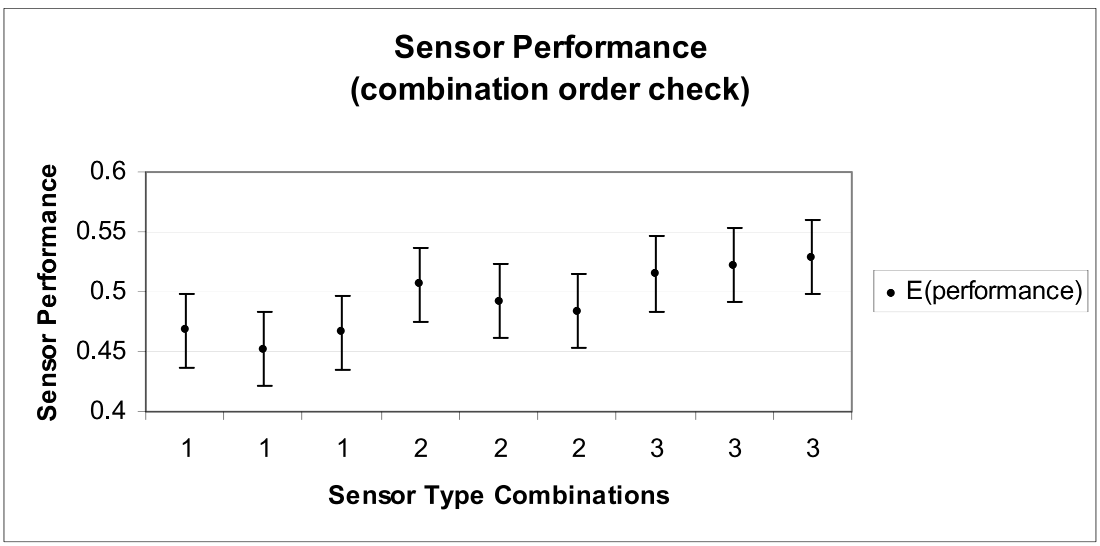

Figure 22. Check Combination Order (Zoom View)

Simulation Run	Sensor Combination	Sensor Type	Response Mean	95% CI Lower	95% CI Upper
1	Sensor 1	1	0.468	0.437	0.499
2	Sensor 2	1	0.452	0.421	0.483
3	Sensor 3	1	0.466	0.435	0.497
4	Sensor 1	2	0.506	0.475	0.537
5	Sensor 2	2	0.492	0.461	0.523
6	Sensor 3	2	0.484	0.453	0.515
7	Sensor 1	3	0.515	0.484	0.546
8	Sensor 2	3	0.522	0.491	0.553
9	Sensor 3	3	0.529	0.498	0.560

Table 3. Experiment C Summary Statistics

The figures above illustrate the results from the table that sensors of the same type yield response means that are not significantly different at $\alpha = 0.05$. In other words, the results are equivalent for sensors of the same type.

F. EXPERIMENT D (IMPROVED SENSOR)

Intuition indicates an improved sensor performs better than the existing sensors. This experiment confirms that intuition, and therefore contributes to verifying the underlying model.

By improving the input sensor specifications of sensor 1 (Appendix A displays the sensor’s improved-type specifications), and by not changing the other sensors’ specifications, the results below verify expectation. They support intuition: sensor 1 and sensor combinations involving sensor 1 outperform the other similar sensor combinations as shown in the figures below. Also,

comparison of the figures below with figures 19 and 20 above illustrate sensor 1's performance changes due to improved specifications. That supports intuition that improved specifications lead to improved performance.

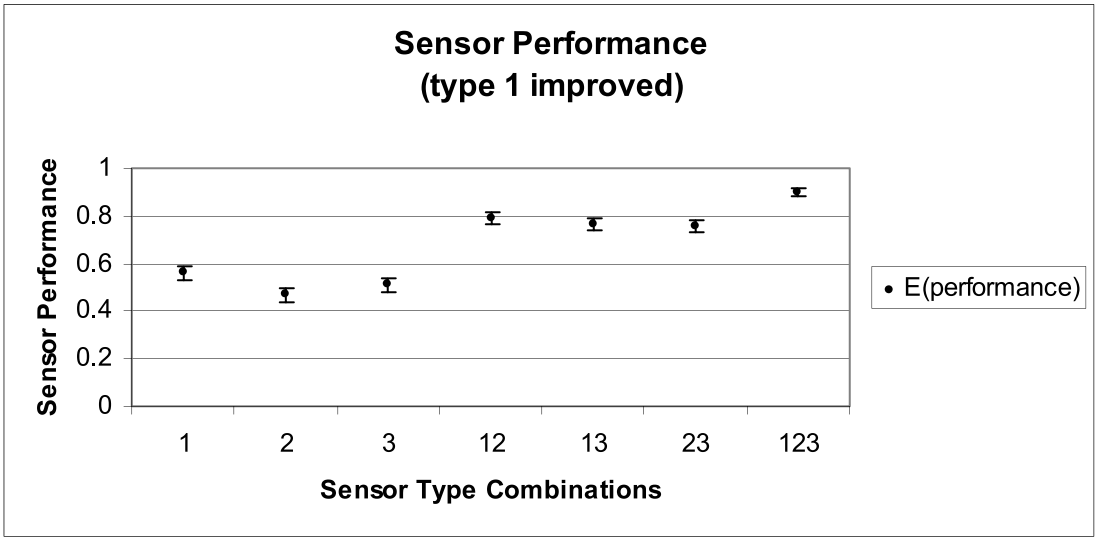

Figure 23. Sensor Performance (Sensor 1 Improved)

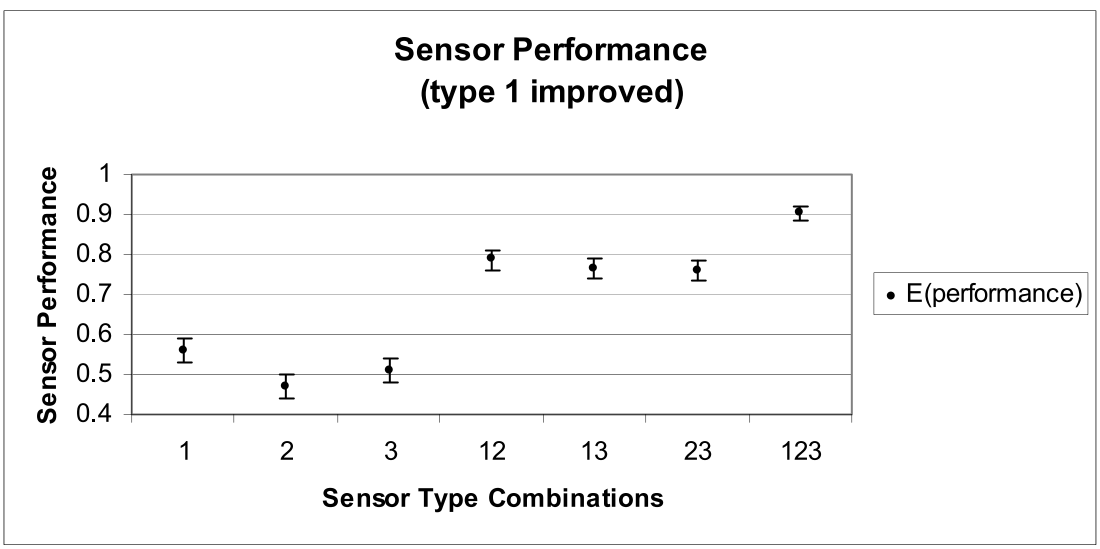

Figure 24. Sensor 1 Improved (Zoom View)

G. EXPERIMENT E (EACH SENSOR TYPE VARIES)

The purpose of this experiment is to demonstrate how the sensor credit apportionment method from this thesis compares performance of multiple sensors (three sensors in this study) of multiple types (three possible types in this study). The experiment yields the results of all combinations of three sensors of three possible types.

This experiment represents how this credit apportionment method assists decision makers visualize possible performance provided by different sensor type combinations for a particular set of input values. Input values needed:

- Sensor specifications (Appendix A)
- Probability a target is present (Appendix B)
- Probability a target attribute is present given a target is present (Appendix B)
- Sensors’ miss distance data (Appendix B)
- Time required for sensor information to reach the commander (Appendix B)

For this thesis we estimated all the input values above; however, historical research or field tests can yield realistic input values for use in future credit apportionment experiments.

This experiment consists of three sensors, each of type 1, 2, or 3. Since the sensor combination order does not affect the response (as explained previously), the following combinations exhaust all possible groups of sensor types.

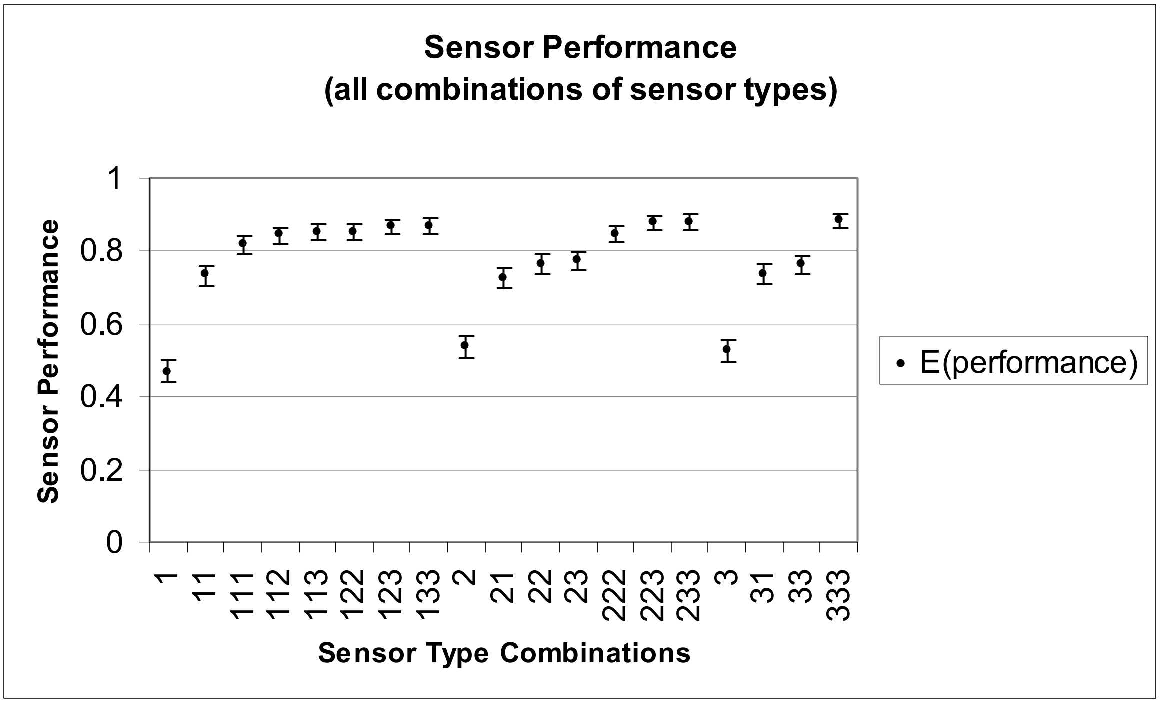

Figure 25. Sensor Performance (Any Sensor Type)

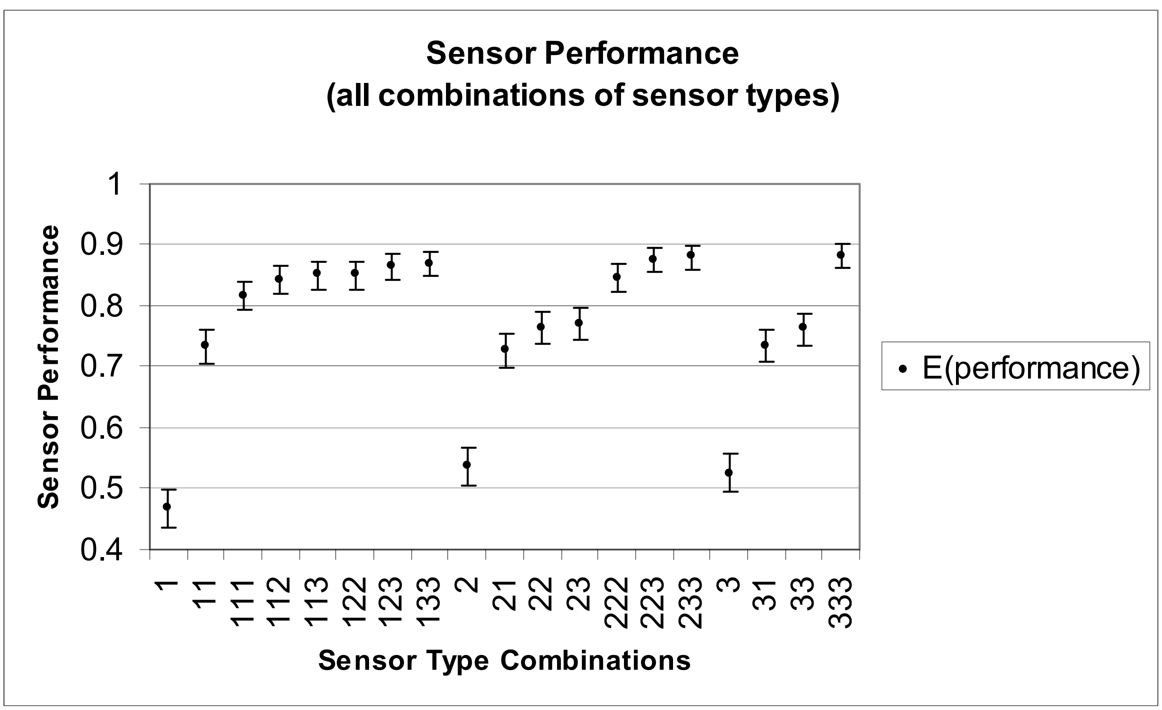

Figure 26. Any Sensor Type (Zoom View)

Simulation Run	Sensor Combination	Sensor Type	Response Mean	95% CI Lower	95% CI Upper
1	Sensor 1	1	0.468	0.437	0.499
2	Sensors 1 & 2	1 & 1	0.734	0.706	0.760
3	Sensors 1 & 2 & 3	1 & 1 & 1	0.817	0.792	0.840
4	Sensors 1 & 2 & 3	1 & 1 & 2	0.844	0.820	0.865
5	Sensors 1 & 2 & 3	1 & 1 & 3	0.851	0.828	0.872
6	Sensors 1 & 2 & 3	1 & 2 & 2	0.851	0.828	0.872
7	Sensors 1 & 2 & 3	1 & 2 & 3	0.866	0.843	0.886
8	Sensors 1 & 2 & 3	1 & 3 & 3	0.870	0.848	0.889
9	Sensor 1	2	0.537	0.506	0.568
10	Sensors 1 & 2	2 & 1	0.727	0.699	0.754
11	Sensors 1 & 2	2 & 2	0.765	0.738	0.790
12	Sensors 1 & 2	2 & 3	0.772	0.745	0.797
13	Sensors 1 & 2 & 3	2 & 2 & 2	0.847	0.823	0.868
14	Sensors 1 & 2 & 3	2 & 2 & 3	0.877	0.855	0.896
15	Sensors 1 & 2 & 3	2 & 3 & 3	0.881	0.859	0.900
16	Sensor 1	3	0.526	0.495	0.557
17	Sensors 1 & 2	3 & 1	0.735	0.707	0.761
18	Sensors 1 & 2	3 & 3	0.763	0.736	0.788
19	Sensors 1 & 2 & 3	3 & 3 & 3	0.883	0.862	0.901

Table 4. Experiment E Summary Statistics

From the figures and table above, all combinations of three sensors (except for the combination of three sensors of type 1) perform best, and yield response means that are not significantly different at $\alpha = 0.05$. Also, all combinations of two sensors yield response means that are not significantly different at $\alpha = 0.05$, and these perform

better than each individual sensor. These results support the idea that multiple sensor combinations provide better performance (or, better assist a commander with decision making) than any single member of the multiple sensor combination acting alone. In other words, multiple sensors provide a synergistic effect on decision making performance.

The individual sensors in this experiment perform very similarly. At $\alpha = 0.05$ sensor type 1 and sensor type 3 provide significantly similar response means. In addition, sensor type 2 and sensor type 3 do not differ significantly at $\alpha = 0.05$. Therefore, for the particular set of input parameters from Appendices A and B, all three sensors provide essentially identical performance in this experiment. In this case we rank all three sensors the same in terms of apportioning credit.

H. MODEL VERIFICATION AND VALIDATION

1. Verification

The Army states that part of the "…verification process…establishes whether the M&S [Model & Simulation] logic and code correctly perform the intended functions" (Army Regulation 5-11, 1997). Similarly, Law and Kelton suggest the following verification technique: "Run the simulation under a variety of settings of the input parameters, and check to see that the output is reasonable" (Law and Kelton, 2000). This thesis implements that technique by varying sensor types among all the experiments. Although all the above experimental results help to verify the underlying logic and code, Experiments C

and D especially indicate appropriate underlying calculations.

2. Validation

The Army defines validation as "…the process of determining the extent to which the M&S [Model & Simulation] accurately represents the real world from the perspective of its intended use" (Army Regulation 5-11, 1997). Assuming the input values for the model represent realistic values reasonably well, the model results agree with what we would expect to find. However, we have examined only a few examples. Therefore, within the set of examples we have examined in this thesis, this credit apportionment model adequately "…represents the real world from the perspective of its intended use" (Army Regulation 5-11, 1997). Or stated another way, each of the experiments above yield results "…consistent with perceived system behavior…" (Law and Kelton, 2000). Law and Kelton define this as face validity.

Although true validation, which requires in part "…high-quality information and data on the system," is not realistically feasible at this time, further research for more realistic model input values would provide a more confident face validation (Law and Kelton, 2000). Law and Kelton also state, "The most definitive test of a simulation model's validity is to establish that its output data closely resemble the output data that would be expected from the actual…system" (Law and Kelton, 2000). Since an actual system to apportion credit to multiple sensors does not exist, "…results validation" is not feasible at this time (Law and Kelton, 2000).

IV. CONCLUSIONS

A. PURPOSE

Recall that this thesis addresses the multiple sensor credit apportionment phenomenon by conceptualizing its process (knowledge), developing a working model (algorithm), and considering required input data (data).

Since very little published information exists about multiple sensor credit apportionment and its inherent processes, a significant portion of this research effort attempts to communicate the essence of the apportioning credit phenomenon and its link to data fusion and information quality.

This thesis focuses on the development of an appropriate algorithm that fuses detection information from independent sources while considering information quality in order to make a decision, assess the decision, and apportion credit. This complex and detailed algorithm forms the basis for a computer simulation. Three model development steps make up the algorithm development process for this thesis:

- determine sensor detection capabilities,
- determine information quality each sensor provides,
- fuse detection capabilities and information value from multiple sensors.

The first model development step determines each sensor's detection capabilities by combining the presence of a target, the presences of target attributes, and the sensor's ability to detect those attributes. This thesis

accomplishes this step by using the law of total probability.

The second model development step determines how much value the sensors' detection information holds for a commander by calculating an information quality value for each sensor. Information quality contains three components in this thesis: accuracy, timeliness, and completeness (Perry, 2000).

The third model development step fuses the results from steps one and two in order to provide information to a commander for decision making. The correctness of the commander's decision based on the actual target state and sensor-provided information provides the measure for comparing performance of various sensor combinations.

Consideration of required input data discovers that the credit apportionment model in this thesis depends heavily on input data. For this thesis, the input data is estimated. Therefore, while this model does not provide realistic performance of each sensor, it does provide insight about the relationships between sensors, the operational decision, and appropriate credit given to the sensors based on their performance.

The examination of this method includes conducting five experiments of various settings of three variables. The variables represent the sensors, and the settings represent the types of sensors. The response and measure of effectiveness for all five experiments is sensor performance. We define sensor performance as the proportion of correct sensor and commander decisions to the total number of replications defines sensor performance.

Each experiment provides verification of the underlying calculations, and provides example output results based on input parameters.

B. FUTURE STUDIES

A more comprehensive representation of the multiple sensor credit apportionment method from this thesis requires future research in several areas.

a. More Detailed Experimental Design

The research effort in this thesis focuses on developing a complex model of a complex phenomenon. The analysis is relatively straightforward in that five experiments are conducted with very few variables in order to demonstrate face-validation of the modeling process. Future research could include using this model for a more comprehensive experiment with numerous variables (the model's input parameters) and examine which are most significant.

b. Weighting Information Quality Components

Varying the weighting of each information quality component (accuracy, timeliness, and completeness) may reveal how each affects decision correctness. For example, if timeliness receives the largest weight for importance, then accuracy and completeness may suffer. Results from different weighting may lead to alternate apportionment of credit than when we hold all weights equal.

c. Operational Factors

Army professionals describe operations in terms of Mission, Enemy, Terrain, Troops, and Time Available (METT-T) in order to plan and execute better operations (FM 101-5, 1997). Incorporating operations data into the model by

means of an operational factor or a set of factors would represent the operational environment that the sensors operate in. METT-T provides a good breakdown of an operation; therefore, operational factors representing METT-T may yield more meaningful results for Army decision makers. The critical—and difficult—portion of this idea consists of using realistic operations data for the operational factors.

d. Commander Learning

Incorporating learning (or experience) in a future version of the model could provide a better representation of a commander’s decision making. The present model assumes a commander makes an operational decision based on sensors’ current reported information, and not on sensors’ previous performance. In reality, a commander makes a decision based on many factors, including experience with similar sensors and their previous performance.

e. Generalize Code

The model and simulation for this thesis are tied to three or fewer sensors with three or fewer types, one target, and three or fewer target attributes. Larger-scale sensor performance comparison requires the ability to accommodate greater quantities of sensors, sensor types, targets, and target attributes.

f. Spreadsheet Version

Although the simulation implementing this thesis’ model was coded in Java, a spreadsheet version is also possible. A spreadsheet version may provide an easier environment to anyone desiring to examine, understand, or adjust the model’s underlying relationships and

calculations. However, a spreadsheet version is not conducive to scaling up.

The Java source code for the model and simulation in this thesis is available by contacting CPT Mason Crow, United States Military Academy, Department of Mathematical Sciences, West Point, New York.

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LIST OF REFERENCES

Bauman, M., “Measures of Merit”, TRADOC Analysis Center Army Workshop, August 2001.

Bishop, Y. M. M., S. E. Fienberg, and P. W. Holland, Discrete Multivariate Analysis, MIT Press, 1975.

Cowell, R. G., A. P. Dawid, S. L. Lauritzen, D. J. Spiegelhalter, Probabilistic Networks and Expert Systems, Springer-Verlag New York, Inc., 1999.

Devore, J. L., Probability and Statistics for Engineering and the Sciences, Duxbury Thomson Learning, 2000.

Jane’s Strategic Weapon Systems, Jane’s Information Group Inc., Issue 35, 2001.

Law, A. M. and W. D. Kelton, Simulation Modeling and Analysis, McGraw-Hill, Inc., 2000.

Marshall, K. T. and R. M. Oliver, Decision Making and Forecasting, McGraw-Hill, Inc., 1995.

Perry, W. L., “Knowledge and Combat Outcomes,” Military Operations Research, V5 N1, 2000.

Ragsdale, C. T., Spreadsheet Modeling and Decision Analysis, South-Western College Publishing, 2001.

Sanchez, S. M., P. J. Sanchez, and J. S. Ramberg, “A Simulation Framework for Robust System Design,” in Concurrent Design of Products, Manufacturing Processes and Systems, ed. B. Wang. Gordon and Breach, 1998, 279-314.

United States Army, “White Paper: Concepts for the Objective Force,” Headquarters Department of the Army, Washington, D.C., 2001.

United States Army, Army Regulation 5-11, “Management of Army Models and Simulations,” Headquarters Department of the Army, Washington, D.C., 1997.

United States Army, Field Manual No. 101-5, “Staff Organization and Operations,” Headquarters Department of the Army, Washington, D.C., 1997.

United States Army, Field Manual No. 6-20-10, “Tactics, Techniques, and Procedures for the Targeting Process,” Headquarters Department of the Army, Washington, D.C., 1996.

United States Army, Field Manual No. 34-130, “Intelligence Preparation of the Battlefield,” Headquarters Department of the Army, Washington, D.C., 1994.

Waltz, E. and J. Llinas, Multisensor Data Fusion, Artech House, 1990.

APPENDIX A. SENSOR SPECIFICATIONS

A. SENSOR TYPE 1

1. Detects attribute 1 best:

- probability sensor detects attribute 1 given attribute 1 present = 0.95
- probability sensor detects attribute 1 given attribute 1 NOT present = 0.10 (false detection)

2. Detects attribute 2 poorly:

- probability sensor detects attribute 2 given attribute 2 present = 0.45
- probability sensor detects attribute 2 given attribute 2 NOT present = 0.25 (false detection)

3. Detects attribute 3 satisfactorily:

- probability sensor detects attribute 3 given attribute 3 present = 0.75
- probability sensor detects attribute 3 given attribute 3 NOT present = 0.20 (false detection)

4. Detects target given detection of attributes:

- probability sensor detects target given sensor detects attributes 1, 2, and 3 = 0.95
- probability sensor detects target given sensor detects attributes 2 and 3 only = 0.75
- probability sensor detects target given sensor detects attributes 1 and 3 only = 0.90
- probability sensor detects target given sensor detects attributes 1 and 2 only = 0.85
- probability sensor detects target given sensor detects attributes 3 only = 0.70
- probability sensor detects target given sensor detects attributes 2 only = 0.60
- probability sensor detects target given sensor detects attributes 1 only = 0.80
- probability sensor detects target given sensor detects no attributes = 0.025

B. SENSOR TYPE 2

1. Detects attribute 1 satisfactorily:

- probability sensor detects attribute 1 given attribute 1 present = 0.60
- probability sensor detects attribute 1 given attribute 1 NOT present = 0.20 (false detection)

2. Detects attribute 2 best:

- probability sensor detects attribute 2 given attribute 2 present = 0.90
- probability sensor detects attribute 2 given attribute 2 NOT present = 0.05 (false detection)

3. Detects attribute 3 poorly:

- probability sensor detects attribute 3 given attribute 3 present = 0.55
- probability sensor detects attribute 3 given attribute 3 NOT present = 0.30 (false detection)

4. Detects target given detection of attributes:

- probability sensor detects target given sensor detects attributes 1, 2, and 3 = 0.90
- probability sensor detects target given sensor detects attributes 2 and 3 only = 0.80
- probability sensor detects target given sensor detects attributes 1 and 3 only = 0.68
- probability sensor detects target given sensor detects attributes 1 and 2 only = 0.87
- probability sensor detects target given sensor detects attributes 3 only = 0.60
- probability sensor detects target given sensor detects attributes 2 only = 0.75
- probability sensor detects target given sensor detects attributes 1 only = 0.65
- probability sensor detects target given sensor detects no attributes = 0.025

C. SENSOR TYPE 3

1. Detects attribute 1 poorly:

- probability sensor detects attribute 1 given attribute 1 present = 0.50
- probability sensor detects attribute 1 given attribute 1 NOT present = 0.30 (false detection)

2. Detects attribute 2 satisfactorily:

- probability sensor detects attribute 2 given attribute 2 present = 0.65
- probability sensor detects attribute 2 given attribute 2 NOT present = 0.15 (false detection)

3. Detects attribute 3 best:

- probability sensor detects attribute 3 given attribute 3 present = 0.97
- probability sensor detects attribute 3 given attribute 3 NOT present = 0.10 (false detection)

4. Detects target given detection of attributes:

- probability sensor detects target given sensor detects attributes 1, 2, and 3 = 0.93
- probability sensor detects target given sensor detects attributes 2 and 3 only = 0.85
- probability sensor detects target given sensor detects attributes 1 and 3 only = 0.80
- probability sensor detects target given sensor detects attributes 1 and 2 only = 0.70
- probability sensor detects target given sensor detects attributes 3 only = 0.77
- probability sensor detects target given sensor detects attributes 2 only = 0.65
- probability sensor detects target given sensor detects attributes 1 only = 0.6
- probability sensor detects target given sensor detects no attributes = 0.025

D. SENSOR IMPROVED TYPE

1. Detects attribute 1 perfectly:

- probability sensor detects attribute 1 given attribute 1 present = 1.0
- probability sensor detects attribute 1 given attribute 1 NOT present = 0.0 (false detection)

2. Detects attribute 2 perfectly:

- probability sensor detects attribute 2 given attribute 2 present = 1.0
- probability sensor detects attribute 2 given attribute 2 NOT present = 0.0 (false detection)

3. Detects attribute 3 perfectly:

- probability sensor detects attribute 3 given attribute 3 present = 1.0
- probability sensor detects attribute 3 given attribute 3 NOT present = 0.0 (false detection)

4. Detects target given detection of attributes:

- probability sensor detects target given sensor detects attributes 1, 2, and 3 = 1.0
- probability sensor detects target given sensor detects attributes 2 and 3 only = 0.66
- probability sensor detects target given sensor detects attributes 1 and 3 only = 0.66
- probability sensor detects target given sensor detects attributes 1 and 2 only = 0.66
- probability sensor detects target given sensor detects attributes 3 only = 0.33
- probability sensor detects target given sensor detects attributes 2 only = 0.33
- probability sensor detects target given sensor detects attributes 1 only = 0.33
- probability sensor detects target given sensor detects no attributes = 0.0

APPENDIX B. INPUT DISTRIBUTION PARAMETERS

A. TARGET PRESENCE PROBABILITY

- Probability target present = uniform(0.0, 0.75)

B. ATTRIBUTE PRESENCE PROBABILITY GIVEN TARGET PRESENCE

1. Attribute 1:

- probability attribute 1 present given target present = triangle(0.6, 1.0, 0.8)
- probability attribute 1 present given target NOT present = triangle(0.1, 0.7, 0.5)

2. Attribute 2:

- probability attribute 2 present given target present = triangle(0.6, 1.0, 0.9)
- probability attribute 2 present given target NOT present = triangle(0.0, 0.4, 0.1)

3. Attribute 3:

- probability attribute 3 present given target present = triangle(0.6, 1.0, 0.75)
- probability attribute 3 present given target NOT present = triangle(0.0, 0.1, 0.0)

C. LOCATION ACCURACY

- Miss distance = normal(0.0, 1.0)

D. TIMELINESS

- Time duration for sensor information to reach commander = exponential(rate = 0.2)

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APPENDIX C. EXPERIMENTAL DESIGNS

A. EXPERIMENT A (ALL SENSORS OF SAME TYPE)

Simulation Run	Sensor 1 Type	Sensor 2 Type	Sensor 3 Type
1	1	NA	NA
2	NA	1	NA
3	NA	NA	1
4	1	1	NA
5	1	NA	1
6	NA	1	1
7	1	1	1

Table 5. Experiment A Design

B. EXPERIMENT B (EACH SENSOR OF UNIQUE TYPE)

Simulation Run	Sensor 1 Type	Sensor 2 Type	Sensor 3 Type
1	1	NA	NA
2	NA	2	NA
3	NA	NA	3
4	1	2	NA
5	1	NA	3
6	NA	2	3
7	1	2	3

Table 6. Experiment B Design

C. EXPERIMENT C (SENSOR COMBINATION ORDER)

Simulation Run	Sensor 1 Type	Sensor 2 Type	Sensor 3 Type
1	1	NA	NA
2	NA	1	NA
3	NA	NA	1
4	2	NA	NA
5	NA	2	NA
6	NA	NA	2
7	3	NA	NA
8	NA	3	NA
9	NA	NA	3

Table 7. Experiment C Design

D. EXPERIMENT D (IMPROVED SENSOR)

Simulation Run	Sensor 1 Type	Sensor 2 Type	Sensor 3 Type
1	1	NA	NA
2	NA	2	NA
3	NA	NA	3
4	1	2	NA
5	1	NA	3
6	NA	2	3
7	1	2	3

Table 8. Experiment D Design

E. EXPERIMENT E (EACH SENSOR TYPE VARIES)

Simulation Run	Sensor 1 Type	Sensor 2 Type	Sensor 3 Type
1	1	NA	NA
2	1	1	NA
3	1	1	1
4	1	1	2
5	1	1	3
6	1	2	2
7	1	2	3
8	1	3	3
9	2	NA	NA
10	2	1	NA
11	2	2	NA
12	2	3	NA
13	2	2	2
14	2	2	3
15	2	3	3
16	3	NA	NA
17	3	1	NA
18	3	3	NA
19	3	3	3

Table 9. Experiment E Design

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INITIAL DISTRIBUTION LIST

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   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California

3. Michael F. Bauman
   Headquarters, TRADOC Analysis Center
   Fort Leavenworth, Kansas

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